KU LEUVEN

ARENBERG DOCTORAL SCHOOL
FACULTY OF ENGINEERING SCIENCE

ENERGY SAVINGS IN THE RESIDENTIAL BUILDING SECTOR

AN ASSESSMENT BASED ON STOCHASTIC MODELLING

Mieke DEURINCK

Supervisor:
Prof. dr. ir.-arch. Staf Roels
Prof. dr. ir.-arch. Dirk Saelens

Dissertation presented in partial fulfillment of the requirements for the degree of Doctor in Engineering Science

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Voorwoord

Ik denk niet dat ik voorbestemd was om een doctoraat te beginnen, laat staan te eindigen. Maar het onderwerp lag me direct nauw aan het hart en dan doet een mens al eens onvoorziene dingen. Wat een geluk dus dat ik gedurende het hele traject zo vaak geholpen en gesteund ben, op bewuste maar nog veel vaker op onbewuste wijze. Niet meer dan logisch dat ik dat hier even op een rijtje zet.

Het is alvast niet uit plichtsbewustzijn, maar wel uit de logica zelve dat ik start met Staf, mijn promotor. Ik kan heel duidelijk zijn: zonder jou als mijn promotor was er geen doctoraat geweest. Die grote vrijheid en dat enorme vertrouwen dat ik kreeg om met zo'n breed onderwerp aan de slag te gaan, de bewonderenswaardige manier waarop jij snel en gericht de hoofd- van de bijzaken kan onderscheiden, de rust en kalmte die je altijd weet te behouden en over te brengen, het begrip dat je aan de dag legde toen het doctoraat me minder goed afging. Allemaal ingrediënten voor een meer dan geslaagd promotorschap, waarvoor dank! Tegelijk was en ben je een inspiratie voor mezelf als mens (en ik ben zeker voor nog vele anderen op onze afdeling!): warm, empathisch, grappig. Het maakt jou tot een atypische academicus en daar kan ik alleen maar erg dankbaar voor zijn!

Een welgemeende dankjewel ook aan Dirk, mijn co-promotor. Jouw input is van onschatbare waarde geweest: je oog voor detail, je kennis van zaken, je kritische ingesteldheid −allemaal elementen die ik heel erg geapprecieerd heb en die dit werk ontegensprekelijk beter gemaakt hebben. Ik heb onze samenwerking steeds als erg aangenaam ervaren en ik onthoud zeker ook de plezante, niet-academische gesprekken bij wat boterhammen en een kop koffie.

En dan de afdeling Bouwfysica zelf. Wat een fijne, aangename plek om te vertoeven en een doctoraat af te werken −sowieso bedankt aan iedereen. Wout, wij gaan al een heel eind mee (als ik grof tel, zo'n 16 jaar reeds) en ik voel me vereerd dat ik reeds heel die tijd zo'n warme, eerlijke en spitsvondige kerel als jij tot mijn vrienden mag rekenen. Ik vergeet alvast nooit die ontelbare korte en lange gesprekken in dat kleine kantoortje van ons en het aanmoedigende mini-eclair'ke dat je mij ooit meebracht van de bakker −merci voor alles! Jelle, hoe tof om met iemand als jij in hetzelfde kantoortje, maar vooral, op dezelfde golflengte te zitten; gewoon door jezelf te zijn maakte jij de dagen zoveel vrolijker, bedankt daarvoor! Barbara, ik weet niet hoe mijn doctoraatsperiode zou verlopen zijn zonder jou erbij als lotgenote én als vriendin. Het deed deugd om de vele wetenschappelijke vertwijfelingen met elkaar te kunnen delen, maar alles daarbuiten met jou kunnen delen was nog veel waardevoller! Jeroen, dankjewel dat ik altijd bij je terecht kon voor (simulatie)raad, gebrainstorm of gebabbel, ik wens je nog het allerbeste toe! Glenn, Ruben en Geert, bedankt voor jullie inspirerende ideeën en vele tips&tricks doorheen mijn doctoraat.

Tenslotte is er nog die grote groep van 'stille' helpers, zij die misschien nooit echt geweten hebben waar ik mee bezig was (sorry mama dat mijn doctoraat een taboe-onderwerp was, ik zal het nooit meer doen), maar die ik –ook al hebben ze geen letter mee geschreven– voor geen geld had kunnen missen. Mama en papa, bedankt voor die onvervangbare thuis: gezellig, af en toe wat chaotisch, maar altijd liefdevol. En papa, dankjewel dat jij misschien wel de kiem van dit hele doctoraat geweest bent: dankzij jou was rationeel en kritisch omgaan met energie een vanzelfsprekendheid in ons gezin, en hoe beangstigend sommige denkbeelden misschien wel waren als klein meisje ('Mieke, ooit is het gedaan met de olie hé'), ik kan alleen maar erg dankbaar zijn voor die basishouding. Broer, jij en ik, dat zijn twee handen op één buik en samen met jou het parcours van school, ingenieur, verbouwing (met aandacht voor energiezuinigheid, dat spreekt!), jonge kindjes,... kunnen en mogen doorlopen, ik had het me nooit leuker kunnen indenken! En dan zijn er nog mijn sympathieke schoonouders, die heerlijke kliek vriendinnen (dat loopt ook al zo'n 20 jaar als een trein, waarvoor dank meiden!), de onvervangbare Jacky, ...

Ik kan niet ontkennen dat de belangrijkste van allemaal reeds vanaf dag één al eens durfde hengelen naar een plaats in het dankwoord ('Dit is toch érg mooi opgeruimd, niet?'), maar kijk –zelfs zonder het gehengel had het hem gelukt. Peter, 10 jaar al ben jij de onwankelbare rots die ik vertrouw en alles toevertrouw. En dat was bij dit doctoraat niet anders. Je was tegelijk mijn grootste motivator en grootste scepticus, en ik had het nooit anders gewild. Ik had misschien liever niet zo vaak onze kindjes moeten missen die laatste maanden, maar tegelijk wist ik dat jij er voor hen was, de fantastische papa van wie ze zo stapelzot zijn –en zo geraakte ook dat gepasseerd.
En dan nu, kwestie van jouw steeds wederkerende vraag af te ronden:

Jij: 'En, hoeveel pagina's heb je vandaag geschreven?'
Ik: 'Goh, toch een kleine 200.'

Mieke, 16 september 2015.

Abstract

Energy savings in the residential building sector are typically predicted by means of simplified, normative calculation tools, relying on standardized user behaviour. In reality however, actual energy savings prove to be only a fraction of these predicted savings, seriously questioning the use of these tools in reliable cost efficiency analyses and robust policy making. Additionally, the tools are mostly used deterministically, giving no insight in the uncertainties inherent to predicting energy savings.

Therefore, the main aim of this work is to provide a more reliable energy saving prediction method, embedded in a probabilistic framework. To do so, an evidence-based probabilistic behavioural model is developed, reflecting the large variety in dwelling use. Key aspects of the final behavioural model are (i) the use of time-dependent occupancy profiles and (ii) the implementation of space-dependent heating patterns. As the simple thermal building models of the normative tools are no longer suitable to implement this behavioural model, a two-zone dynamic generic building model is set up as well. By using the well-known Monte-Carlo technique, energy saving predictions can be generated in terms of probability distributions.

When applied on an existing case study district, the results show how the above methodology is able to predict energy use estimates that are very comparable to measured data (both in average values and statistical spread), confirming its overall reliability. The probabilistic set-up also shows to be worthwhile in assessing energy savings at a large-scale level, since the building parameters can be conceived probabilistic too, thereby capturing the global uncertainty of statistical building stock data.

Korte inhoud

Het voorspellen van energiebesparingen in de residentiële gebouwensector gebeurt meestal met behulp van sterk vereenvoudigde en gestandardiseerde rekenmethoden, vaak in combinatie met 'gemiddeld' gebruikersgedrag. In de praktijk echter blijken de energiebesparingen 20 tot 60 % lager te liggen dan de berekende, waardoor het gebruik van deze rekenmethodes sterk in vraag moet gesteld worden −zeker wanneer ze aangewend worden in kosten-baten analyses en als beleidsondersteunende tool. Tegelijk zijn deze rekenmethoden meestal volledig deterministisch opgevat, waardoor geen inzicht kan verschat worden in de onzekerheden inherent aan het voorspellen van energiebesparingen.

Het doel van dit werk is om een meer betrouwbare en probabilistisch opgevatte rekenmethode te ontwikkelen voor het inschatten van energiebesparingen in de residentiële gebouwenscector. Hiervoor is eerst een probabilistisch gedragsmodel opgesteld, zoveel als mogelijk gebaseerd op empirische data en in staat om de grote veelzijdigheid aan gebruikersgedrag te weerspiegelen. Belangrijkste aspecten zijn (i) het gebruik van tijdsafhankelijke bezettingsprofielen en (ii) de implementatie van ruimte-afhankelijke verwarmingspatronen. Vervolgens is dit gedragsmodel geïmplementeerd in een transient en zonaal gebouwmodel. Door gebruik van de Monte-Carlo techniek tenslotte worden energiebesparingen gegenereerd in de vorm van kansverdelingen.

De resultaten tonen hoe de ontwikkelde methodologie in staat is om gemeten energieverbuiken betrouwbaar in te schatten, zowel gemiddeld als voor het inschatten van de spreiding. Ook is het in staat om effecten van een energiebesparende maatregel weer te geven die bij een vereenvoudigde rekenmethode onzichtbaar blijven (zoals bijv. temperature takeback) . Tenslotte levert de probabilistische set-up een belangrijke bijdrage aan het inschatten van energiebesparingen op een geagreggeerd gebouwstockniveau (wijk, stad, regio, . . .). Aangezien ook de gebouwkenmerken probabilistisch kunnen opgevat worden, kan de onzekerheid, inherent aan statistische gebouwstockdata, beter geïntegreerd worden in de uiteindelijke voorspelling.

Contents

Nomenclature

Acronyms

ecdf	empirical cumulative distribution function
ECS	Energy Consumption Survey
EPBD	Energy Performance of Buildings Directive
EPR	(Belgian) Energy Performance Regulation
HDD	Heating Degree Days
HoH	Head of the Household
LHS	Latin Hypercube Sampling
TRV	Thermostatic Radiator Valves

Subscripts

50	at 50 Pa air pressure difference
a	air
a	annual
calc	calculated
e	exterior
heat	heating
i	interior
inf	infiltration
m	mean
m	monthly
meas	measured
norm	normalised
op	operative
rad	radiative
ref	reference
tot	total
vent	ventilation

Greek symbols

α	significance level	-
Δ	difference	
η	efficiency	-
η	utilization factor	-
μ	mean	n.a.

ρ	Spearman's rank correlation coefficient	-
ρ	density	kg/m^3
σ	standard deviation	n.a.

Roman symbols

$\bar{x}$	sample mean	n.a.
$\dot{V}$	volume flow	m^3/h
A	area	m^2
C	air leakage coefficient	m^3 /(h Pa^n)
C	compactness	m
C	correlation matrix	-
E	amount of energy	J ; kWh
g	solar factor of glazing	-
H	specific transmission heat losses	W/K
m	m-factor for ventilation systems	-
N	normal distribution	n.a.
n	air change rate	1/h
n	air flow exponent	-
n	amount of runs	-
n	sample size	-
P	perimeter length	m
P	pressure	Pa
p	p-value	-
Q	energy flow	W
R	thermal resistance	m^2K/W
r	Pearson's product-moment correlation coefficient	-
s	sample standard deviation	n.a.
T	temperature	$^\circ$ C
U	thermal transmittance	$W/(m^2K)$
V	volume	m^3

1 Introduction

"Remember that all models are wrong;
the practical question is how wrong do they have to be to not be useful."
Box and Draper (1987)

1.1 Context and problem statement

Many European member states have engaged themselves to reach the "20/20/20" climate/energy targets, set by the Europe 2020 strategy (European Commision Communication 2010): 20 % less greenhouse gas emissions compared to 1990, 20 % increase in energy efficiency and 20 % of end energy from renewables. Due to the significant share of residential energy use in the final country end energy use (e.g. 35 % in Belgium in 2010 (FOD ECONOMIE 2010)), policy makers often refer to the high energy saving potential of the existing residential building stock. This is no surprise, since in many countries this building stock is largely outdated and performs badly due to uninsulated walls, single glazing in leaky window frames, uninsulated slab-on-ground floors, energy consuming oil or gas boilers (Itard et al. 2008). To renovate this housing stock in an energy efficient way, large renovation programmes have been and are still being set up.

At the aggregated level (city, district, regional, national, ...) many different actors have special (financial) interest in the outcome of these energy efficient refurbishment schemes: national energy policymakers, local authorities, (social) housing companies, energy service companies (ESCo - financing the retrofit and being refunded by the house owner through a monthly fee (Hannon and Bolton 2015)), etc. An economic cost-benefit analysis, as performed by Verbeeck and Hens (2005), Kumbaroglu and Madlener (2012) or Rysanek and Choudhary (2013), is typically performed beforehand. It offers insight in the cost efficiency of the different retrofit measures and provides a decision basis whether investments should be made and if so, which hierarchy in retrofit measures should be followed, whether grants or subsidised loans should be provided etc. One of the key parameters in every economic analysis is the *estimation of the benefits, being the amount of energy saved*. If the energy savings for a specific refurbishment measure are underestimated, it can undeservedly be eliminated from the list of economically viable measures. If overestimated, the actual return-on-investment rate might be much lower than expected.

To estimate the energy saving potential for a larger group of buildings, like districts or an entire national housing stock, housing stock models are often constructed following the *engineering-based bottom-up approach* (Swan and Ugursal 2009, Kavgic et al. 2010). A schematic representation of this approach is given in Figure 1.1. It relies on a set of dwellings, representative for the considered housing stock, for which a building energy calculation is performed to assess the energy savings ΔE_i for each of the dwellings i. These results are then extrapolated to represent the region or nation, based on the representative weights a_i of the modelled set (Swan and Ugursal 2009).

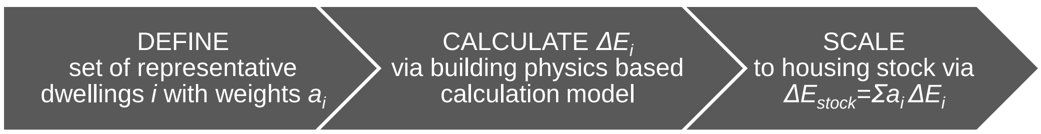


Figure 1.1: Typical workflow within an engineering-based based bottom-up housing stock model to estimate the energy saving potential of a housing stock.

Many such housing stock models are already available e.g. Hens et al. (2001), Firth et al. (2010), McKenna et al. (2013), Cyx et al. (2011) and are frequently used by policy makers to evaluate the effect of possible energy efficient retrofitting measures. However, two aspects undermine the overall reliability of the current housing stock models: (i) the *poor accuracy of the predicted energy savings* ΔE_i and (ii) the *lack of a probabilistic approach*. Both are discussed hereunder.

First, the reliability of the housing stock prediction is, to a great extent, dependent on the accuracy of the energy savings at dwelling level, ΔE_i. If, at this dwelling level, the energy saving predictions ΔE_i are significantly wrong, the errors are propagated and magnified throughout the building stock prediction. In most European countries, ΔE_i is determined by means of the national calculation tool for building energy labelling (Laurent et al. 2013). Many of these tools have been put into force within the framework of the European Energy Performance of Buildings Directive (EPBD (2010)) and are therefore widely known and easily accessible. In addition, they are frequently used for policy making: as imposed by the EPBD, every European Union member state regularly has to revisit its minimum energy performance requirements for existing buildings by using their energy labelling tool in the determination of the cost-optimal renovation levels. In many retrofit studies, however, actual energy savings are frequently found to be 20 to 60 % less than those predicted (Henderson et al. 2003, Hong et al. 2006, Oreszczyn et al. 2006, Hong et al. 2009, Rogan and Gallachóir 2011). This discrepancy between theoretical (ΔE_{calc}) and measured (ΔE_{meas}) energy savings is denoted as **shortfall** (Sorrell et al. 2009) and mathematically formulated as:

$$\text{shortfall} = \frac{\Delta E_{calc} - \Delta E_{meas}}{\Delta E_{calc}} = 1 - \frac{\Delta E_{meas}}{\Delta E_{calc}} \qquad [-] \tag{1.1}$$

A shortfall of e.g. 40 % means that 40 % of the initially estimated energy savings have not been achieved. This phenomenon is of course highly undesirable in the framework of reliable cost efficiency analyses and robust policy making and hence seriously questions the use of these tools for prediction purposes. So, instead of being based on energy labelling tools, the housing stock models should be able to rely on an improved building energy calculation method, capable of assessing more realistic energy savings. As such, **the development of an improved energy saving prediction method, applicable in housing stock models**, forms the first aim of this thesis.

Second, the reliability of the housing stock prediction is also dependent on the model's capability of incorporating uncertainty and variability. Typically, when constructing a housing stock model, many assumptions have to be made, both in the absence of direct data and in the application of input values for which only few supporting data are available (Kavgic et al. 2010). Also, simplifications of reality are needed to keep the housing stock model manageable, for instance by using only a limited set of dwellings to represent the large variation of building forms and characteristics. A similar simplification is performed regarding the user behaviour. Typically, and as done in the energy labelling tools, a single standard user is assumed and implemented in all dwellings. As will be shown in Chapter 3 however, user behaviour in dwellings proves to be highly variable and uncertain and hence forms, amongst others, a major source of variability housing stock models have to deal with (Swan and Ugursal 2009, Kavgic et al. 2010). The current deterministic set-up of housing stock models cannot capture this variability, nor can it incorporate the many modelling uncertainties within the final energy saving estimate of the housing stock. This lack of a probabilistic approach is an important limitation when aiming for robust policy making (Kavgic et al. 2010, Booth et al. 2011). Therefore, the shift should be made from a deterministic to a probabilistic approach, allowing to generate energy saving predictions as a probability distribution rather than as a single, deterministic value. As such, **incorporating a probabilistic approach within the bottom-up housing stock modelling framework**, forms the second aim of this thesis.

1.2 Shortfall in energy savings: case study Spiere

To comprehensively illustrate the aspects that play a role in shortfall at dwelling level, a Belgian case study, monitored both before and after retrofit, is briefly discussed here. The monitoring campaign has been performed on behalf of *Wienerberger NV* - www.wienerberger.be. More elaborated results can be found in Deurinck and Roels (2013).

The starting point is a freestanding dwelling (Figure 1.2a), built in 1901, with uninsulated walls, roof and floor, single glazing in old and air-leaky wooden frames and no ventilation system. Also, mould growth was detected at the inside surface of some outer walls. Apart from the replacement of a few windows and the installation of a condensing gas boiler (feeding the 3 only radiators in the house), no other renovation measures have been taken before 2014 to improve the low energetic performance of the original dwelling.

(a) Front facade, before renovation.

(b) Front facade, after renovation.

Figure 1.2: Renovation case study in Spiere, Belgium. Source: Deurinck and Roels (2013)

During the summer of 2014, an in-depth energy renovation scheme was performed, with the main focus on the extensive insulation (roof, floor, wall and new windows) and improved airtightness of the building envelope (Figure 1.2b). Also, additional radiators were placed and an exhaust ventilation system was installed. The impact of these renovation measures on the energy use for space heating was predicted by the calculation method of the Belgian Energy Performance Regulation (EPR 2010). In this method, several default assumptions are made, like the whole protected volume being continuously heated to 18 °C and internal gains and ventilation rates given only as a function of protected volume. The annual energy use for space heating was predicted to drop from 91 972 kWh to 14 448. Or, the renovation project was expected to lead to a reduction of space heating energy use by a factor 6.

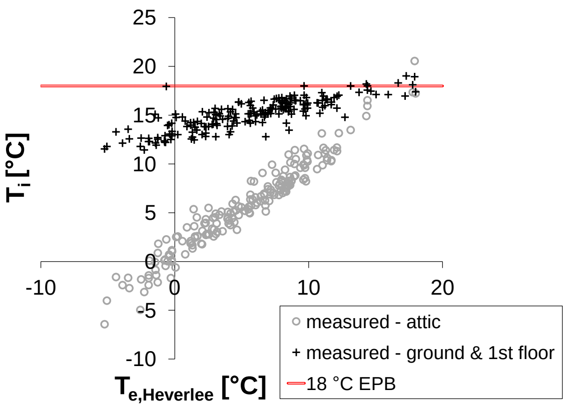
The reality, however, proves to be different. The renovation project was intensively monitored before (heating season 2013-2014) and after retrofit (2014-2015), with the inhabitants (a young couple) remaining the same. An annual energy use for space heating of only 9 492 kWh was found before retrofit[1]. This is less than half of the Flemish averaged household energy use (20 934 kWh per year) for space heating (VREG 2015), and about 10 times less than the aforementioned initial energy use predicted by EPR (2010). After renovation, the annual energy use for space heating[1] dropped to 5 536 kWh, or a reduction by a factor of almost 2.

Similarly as in many other retrofit studies, a large discrepancy is observed between the calculated and measured energy savings. How can this shortfall in energy savings be explained?

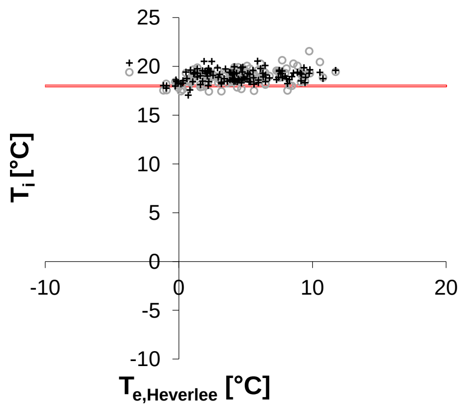
An often cited explanation is the **rebound effect** (Herring and Roy 2007, Greening et al. 2000, Sorrell and Dimitropoulos 2008, Sorrell 2009). After an energy efficient retrofit measure, space

[1] After weather normalisation to the outdoor temperatures of EPR (2010) via heating degree days.

heating gets more affordable. Influenced by the lower energy cost, the inhabitants tend to increase their comfort level, thereby offsetting part of the theoretical energy saving. This economically driven, behavioural change is mainly reflected in increasing the set temperature, heating more rooms more often, etc. Rebound is therefore often used interchangeably with **temperature takeback** (Sorrell et al. 2009, Hamilton et al. 2011, Deurinck et al. 2012), a phenomenon where thermal retrofits lead to an increase in internal temperature. Changed user behaviour is indeed a possible explanation for an indoor temperature rise. However, and as will be shown in the next chapter, it is also due to physical changes, as after retrofit the temperature in the unheated zones get unintentionally higher and the temperature drop between two heating periods gets smaller (Deurinck et al. 2012) −making the rebound effect part of, yet not equal to, the temperature takeback. When looking at the measured indoor temperatures of this case study in Figure 1.3, temperature takeback is indeed observed. For this retrofitting campaign, the inhabitants are not to blame for the temperature takeback: on explicit request of Wienerberger NV the inhabitants maintained their pre-retrofit heating pattern (using only 3 radiators at the original location) throughout the whole measurement campaign. Reasons thus need to be sought in a physical temperature rise, reinforced by the fact that after retrofit the hallway is in open connection from ground floor to attic.



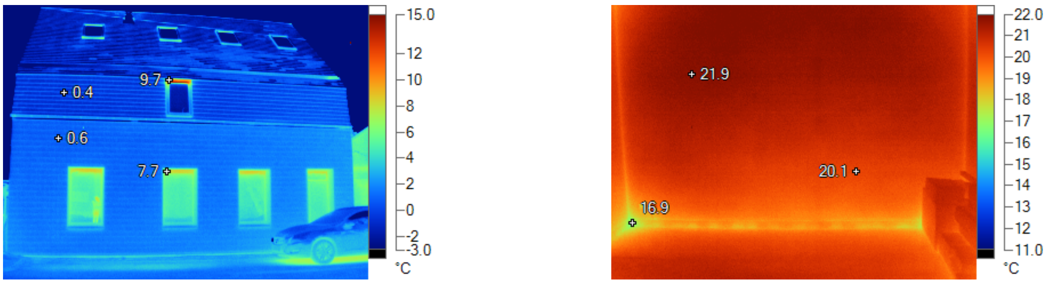
(a) before retrofit



(b) after retrofit

Figure 1.3: Empirical evidence of temperature takeback at the Spiere case study: daily mean indoor temperatures (as a function of daily mean outside temperatures) are higher after retrofit.

Apart from the inhabitants, **technical issues/shortcomings** form another important factor of shortfall. For this particular case study, measurements on the airtightness of the building envelope have shown how the airtightness after retrofit was not as good as expected. Despite the airtightening measures, taken throughout the whole renovation process, the actual infiltration rate at 50 Pa air pressure difference was still 5 air changes per hour, while a value of 1 was aimed for. Additionally, the condensing gas boiler, installed before the building fabric insulation took place, is now subject to a lower heat demand, possibly leading to a drop in overall heating system efficiency (Peeters et al. 2008). Poor design and/or bad workmanship are also possible contributors to shortfall, i.e. insufficient attention to solve thermal bridging throughout the design and execution process, inaccurate placement of building envelope insulation, . . . For this case study, they are believed to be of minor importance: the infrared pictures after retrofit show satisfyingly uniform surface temperature distributions and no signs of major and/or unexpected thermal bridging (Figure 1.4).



(a) Outer view of front nothern facade

(b) Inner view of junction external eastern wall with ground floor

Figure 1.4: Examples of the infrared pictures taken after renovation of the Spiere case study house (clear sky, T_e = ± 0 °C, T_i = ± 22 °C throughout whole dwelling)

Even though the rebound effect/temperature takeback and/or technical shortcomings are a plausible explanation for shortfall, it is doubtful that they alone can explain the large shortfall. One should also question the predictive power of the building energy calculation method used: is it capable of assessing realistic energy use in the first place? If not, one can hardly expect it to produce reliable energy saving predictions.

For this case study, it is immediately clear how the calculation method fails to do so: the Belgian normative calculation method overestimates the pre-retrofit energy use for space heating by a factor 10. The reasons are manyfold. The pre-retrofit indoor temperatures appear to be much lower than the 18 °C as assumed by the normative method (Figure 1.3). This is no surprise, because the inhabitants clearly applied only a minimal level of heating to reduce heating costs. Also, no ventilation system was originally present, so the default ventilation rates, inherent to the method and designed to characterise air change rates in newly built dwellings, are a severe overestimation of the pre-retrofit air change rates. Finally, internal gains have been expressed as a function of protected volume only, thereby ignoring that the dwelling is only minimally inhabited (a young couple being away during the day).

The Belgian normative method, with its default assumptions concerning dwelling use, seems inappropriate to assess realistic energy use, not only for this particular case but also in a larger Belgian context (Hens et al. 2010). A similar conclusion is drawn in many other European countries (Loga et al. 2011, Sunikka-Blank and Galvin 2012, Laurent et al. 2013): national energy performance assessment methods systematically fail in quantifying the actual energy use of dwellings. This lack of predictive power of these methods is shortly called the **energy performance gap** (Sunikka-Blank and Galvin 2012, Galvin 2014b, de Wilde 2014) and mathematically formulated as:

$$gap = \frac{E_{calc} - E_{meas}}{E_{calc}} = 1 - \frac{E_{meas}}{E_{calc}} \quad [-] \tag{1.2}$$

This gap is typically larger for poorly insulated, non-retrofitted houses for which values of 50 % are found (see 2.4.3): the actual energy uses of these houses are found to be only half of the calculated ones. Given this large overestimation of pre-retrofit energy use, it is of course no surprise that also the actual energy savings are overrated. Hence, this performance gap forms an important aspect in the overall shortfall.

In the previous analysis, shortfall is attributed to 3 main causes: rebound, technical shortcomings and the energy performance gap. In the next chapter, a more detailed analysis of each of these causes will be given. For now, it is useful to look at the schematic representation of shortfall, as shown in Figure 1.5.

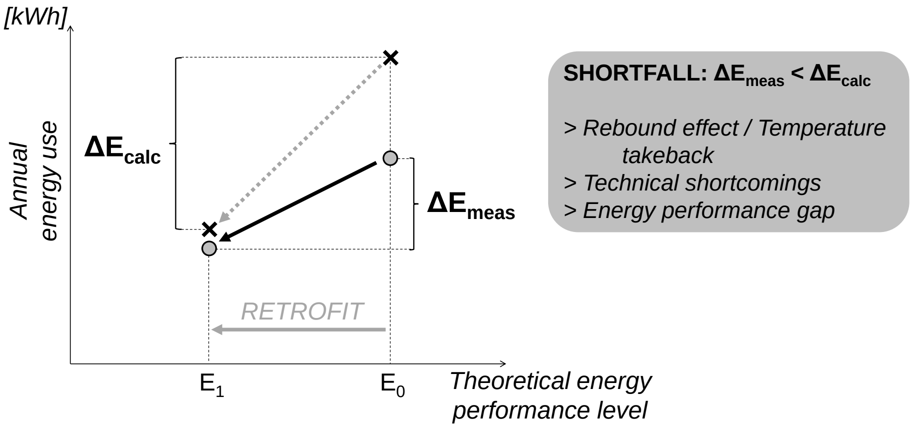


Figure 1.5: Schematic representation of shortfall, being the discrepancy between measured (ΔE_{meas}) and calculated (ΔE_{calc}) energy savings.

Figure 1.5 helps in clarifying the widespread confusion between shortfall and the rebound effect. In the literature, shortfall is often misleadingly assumed to be caused only by the inhabitants changing their behaviour, as is done for example by Haas and Biermayr (2000). This is not true: when theoretical energy savings are not fully achieved, the rebound effect is a possible explanation, yet certainly not the only one.

More importantly, Figure 1.5 clarifies why actual energy savings are so easily overestimated: it is a combination of (i) a large overestimation of pre-retrofit energy use and (ii) a smaller overestimation of post-retrofit use (when shifting towards passive house standards, energy uses are even typically higher than expected (Sunikka-Blank and Galvin 2012)). While the post-retrofit error is commonly cited by means of the rebound effect or technical shortcomings, the pre-retrofit error is often forgotten and could be much more important. With much lower pre-retrofit energy uses than estimated, it is no surprise that the expected level of energy savings cannot be achieved. Or, as stated by Sunikka-Blank and Galvin (2012), "*retrofits cannot save energy that is not actually being consumed*". This is supported by the observation of Henderson et al. (2003) that, the higher the overestimation of the pre-retrofit energy use, the higher the shortfall. Tackling this pre-retrofit energy performance gap thus strongly contributes to reducing shortfall. As such, **reducing the pre-retrofit performance gap** will form a major point of attention throughout this thesis.

1.3 Objectives

The overall research objective is to come to **more reliable energy saving predictions in the residential building sector at the aggregated level**. The term '*reliable*' should be interpreted twofold.

On the one hand, it means '*reliable at the dwelling level*'. There is no use in sticking to simplified, normative energy labelling tools, if they have proven to systematically overestimate the (pre-retrofit) residential energy use. Only if the errors at the dwelling level show to be of random nature, one can be confident of having a tool reliable for use in a bottom-up modelling framework. This leads to:

- **Objective 1: development of an improved probabilistic predictive model of energy use for space heating, applicable in bottom-up housing stock models**

  Due to the importance of a correct user behaviour modelling in the pre-retrofit energy performance gap (see Chapter 2), much effort will be put in the development of a *probabilistic and evidence-based behavioural model*, reflecting real-life dwelling use. The probabilistic set-up is needed to capture the wide variety in user behaviour, while the evidence-based approach allows to make the generated user profiles representative for user behaviour at a (Belgian) national scale. As the simple thermal building models of the energy labelling tools are no longer suitable to implement this user behaviour, *a two-zone dynamic generic building model* will be developed as well, allowing for the easy generation of many different dwelling models.

On the other hand, reliable means '*representative at the large-scale level*'. The predictions should be able to reflect the intrinsic uncertainty and variability, inherent to housing stocks and their models, implying that the shift should be made from a deterministic to a probabilistic approach:

- **Objective 2: incorporation of a probabilistic approach within a bottom-up housing stock framework**

  A global framework will be set in which also the housing stock characteristics are conceived probabilistically. By doing so, insight will be given in the wide variability of energy savings, due to the large uncertainty concerning user behaviour and housing stock dwelling characteristics.

Research scope

With a research domain being as wide as '*estimating energy savings in the residential building sector*', it is logic that boundaries have to be set. These are as follows:

- The domestic energy use associated with hot tapwater production, cooking, lighting and appliances is not considered. The focus is put on thermal renovation measures, tackling the building envelope and the heating system; so only the energy use for space heating is taken into account.

- Renewable energy resources, like photovoltaic panels or solar water heating, are not considered.
- In this work more reliable energy saving predictions are in the first place aimed at by correctly estimating the pre-retrofit energy use. This means that, for example, the modelling of different heating and ventilation systems is kept rather general. Even though a large range of possible new and sophisticated systems exist, it is not the aim of this research to model in detail the impact of each of these technologies on the energy use. Instead, it is the large decrease from a previously poorly performing heating system and/or absence of a ventilation system to an afterwards energy efficient heating and/or ventilation system that is looked for, with additional differentiations between newly installed systems being of minor importance in this work.
- Although the bottom-up approach requires a reliable modelling method at dwelling level, it is not the aim of this research to accurately estimate the energy use for one particular case study, with specific inhabitants and specific boundary conditions. Yet, it is the aim to more reliably generate the energy use distribution of a dwelling, be it fictitious or not, that is believed to be representative for a substantial part of the building stock.
- No economical cost-benefit analysis is performed in this research work. The scope is limited to obtaining reliable benefit estimations, being the energy savings, that can serve as input to such an analysis.

1.4 Outline

Chapter 2 provides in an overview of the shortfall state-of-the-art. The importance of a correct user behaviour modelling in reducing shortfall will be highlighted.

In **Chapter 3** a probabilistic behavioural model for space heating is developed. Whenever possible, the user behaviour actions are based on extensive empirical evidence, found both in the literature and in the analysis of proper empirical data. Key aspects of the final behavioural model are (i) the use of time-dependent occupancy profiles and (ii) the implementation of space-dependent heating patterns (frequent heating in dayzone, less frequent/no heating in nightzone).

To translate this behavioural model into correct building energy simulation, a transient simulation environment is necessary, providing in at least a two-zone building model. This is done in **Chapter 4**, together with some methodological refinements compared with the Belgian energy performance assessment method. The building model is defined as generic as possible to enable easy implementation of different building typologies.

Chapter 5 evaluates the outcome of the combination of the probabilistic behavioural model and the generic building model. To do so, a Belgian case study district is used and 4 different paths are followed: (i) the minimal sample size of the probabilistic analysis is determined, still allowing for a reliable characterisation of the output distribution; (ii) a sensitivity and uncertainty analysis is performed to gain insight in how the behavioural model affects the energy use for space heating; and finally, the computed outcome for a sample of dwellings is compared both to (iii) measured data and (iv) the Belgian energy performance assessment method.

While the previous chapters focused on the development of an improved prediction method at dwelling level, **Chapter 6** places this probabilistic prediction method in the broader framework of housing stock models. A technique is proposed and investigated, called the *stochastic* technique, which captures both the user behaviour variety and building form heterogeneity within the same probabilistic sampling scheme. Due to the available probabilistic behavioural model and the generic set up of the building model, this technique proves to be a time-efficient and straightforward way of generating a housing stock estimate, independently of the scale desired (city/district/regional/national) and offers at the same time valuable insight in how the energy uses and savings are spread across the housing stock considered. In addition it is demonstrated how this stochastic technique can be fitted within a second-order uncertainty quantification scheme, meant to assess the global uncertainty on the housing stock predictions and as such being of great value for robust policy making.

Finally, the main conclusions and contributions, as well as the limitations and possible paths for future research, are discussed in chapter **Chapter 7**.

2

State-of-the-art: shortfall

In this chapter, more detail is given about the shortfall in energy saving retrofitting projects. Firstly, the terminology used is briefly clarified. Secondly, some aspects are discussed about how the term 'energy savings' should be interpreted. Afterwards, an overview is given of the literature review concerning the empirical evidence of shortfall. In the final section, the different possible causes for shortfall are listed and discussed.

2.1 Terminology

In the literature, when describing energy efficient refurbishments in the residential sector, many different terms and metrics are used to describe many different phenomenons. Terms like shortfall (Sorrell et al. 2009), rebound effect (Greening et al. 2000), energy savings deficit (Galvin 2014b), service factor (Haas and Biermayr 2000), comfort factor (Henderson et al. 2003), reduction factor (Sanders and Phillipson 2006), prebound effect (Sunikka-Blank and Galvin 2012), intensity factor (Cayre et al. 2011), energy performance gap (Galvin 2014b, Magalhães and Leal 2014), . . . are often used interchangeably, leading to persistent confusion.

For clarity, and as already mentioned in the introduction, the following terminology and metrics are used within this research work:

shortfall the relative difference between the calculated, theoretical energy savings, ΔE_{calc}, and the actual measured energy savings, ΔE_{meas}; see Equation 1.1. A shortfall of e.g. 40 % means that 40 % of the initially estimated energy savings have not been achieved. Formulated like this, it is identical to the ’reduction factor’ of Sanders and Phillipson (2006) and the ’comfort factor’ of Henderson et al. (2003).

energy performance gap the relative difference between the calculated, theoretical energy use, E_{calc}, and the actual, measured energy use, E_{meas}; see Equation 1.2. A performance gap of 40 % means that the actual energy use is 40 % lower than predicted. When formulated like this, the energy performance gap is equal to the ’prebound effect’ as proposed in the well-documented overview of Sunikka-Blank and Galvin (2012). However, the term ’prebound effect’ is not used here, as it only adds to the common confusion with rebound.

The shortfall and performance gap are defined very similarly, yet they are not equal. While shortfall is solely observed after a refurbishment has taken place, the performance gap is observed in all kinds of situations where theoretical and actual performance are involved, be it pre- or post-retrofit.

2.2 Evaluating energy savings

Since the shortfall is entirely dependent on both the calculated and the actual energy savings, it is at first essential to know how both terms have to be interpreted. If it is not clear how they have been defined/estimated, it is hard to compare different shortfall values between different energy efficiency programs. Also, one has to be aware that there is no such thing as the ’one and only true energy saving’, either measured or calculated. Both are highly dependent on the availability and quality of the data, the normalization methods and engineering models used, the assumptions made by the analysts and modellers etc. As such, this section briefly points out how both the actual (2.2.1) and calculated (2.2.2) energy savings should be interpreted.

2.2.1 Measuring energy savings

Different approaches possible

The most intuitive way of assessing energy savings is via a *longitudinal study*. In this type of studies the same individuals are observed over different study periods, or, applied to the residential retrofit context, the same set of dwellings is followed both before and after retrofit. The actual energy savings are then defined as the difference between the monitored energy use before and after the retrofit, both normalised to standard weather conditions (see horizontal relation in Figure 2.1). The case study of Spiere, described in the introduction, is a typical of example of a longitudinal study on an individual dwelling. The main advantage is that the energy use differences observed are most likely to be the result of the retrofit upgrades to the dwellings, since many other disturbing parameters like dwelling or inhabitant variation in the population before and after are (partly) controlled for. However, by doing so, one implicitly assumes that all conditions, apart from retrofit measures and the outside weather conditions, remain unchanged between the two monitoring periods. In reality, different monitoring periods could be subjected to a different household composition or different household activities, but also to a different economic climate, thereby impacting for example the

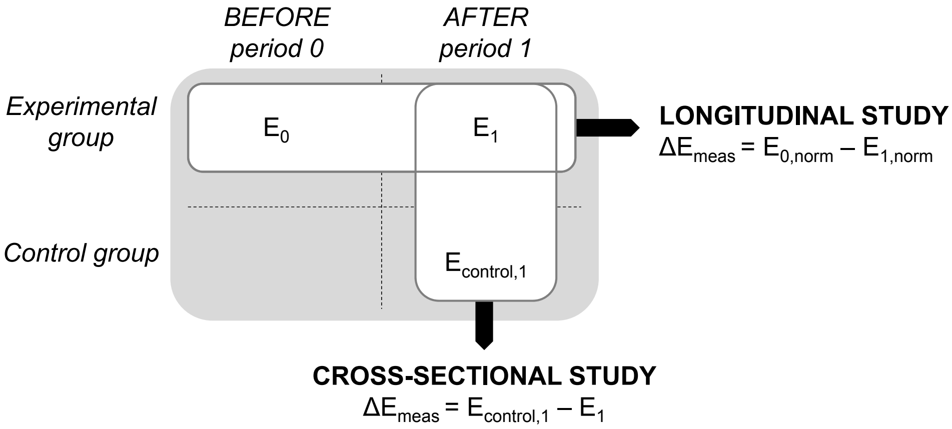


Figure 2.1: Schematic overview of the actual measured energy savings: two possible approaches.

energy behaviour of the observed households. So, it is possible that the observed change in energy use is also explained by other external (economical) factors. Nevertheless, this macro-effect of a changing economic situation on the observed energy savings is most often neglected in typical evaluation studies.

Another way of defining the actual energy savings is by looking at only one specific monitoring period and by comparing the retrofitted group with a control group where no measures have been taken (see vertical relation in Figure 2.1). This is called a *cross-sectional study* (Sommerville 2007). By doing so, the monitoring periods of both groups can be identical and thus, many external factors like the weather conditions and the economic climate are controlled for. However, it is substantial that the experimental and control group have very similar characteristics, not only concerning the main building parameters like dwelling size and insulation quality, but also concerning the socio-economic factors like e.g. household size, income, education, ... (SRC International AIS (Denmark) et al. 2001) If not, it remains unclear whether any difference in energy use, observed between both groups, is to be attributed to the retrofit upgrades themselves or to any differences in characteristics between both samples. Also, in contrast to the longitudinal study where a limited sample might be sufficient, the sample sizes of both the experimental and control group need to be sufficiently large to obtain a statistically significant outcome. This is often unfeasible in practice due to time and budget constraints. Therefore, although the use of a control group methodologically leads to more robust conclusions, it is only rarely done.

Limitations of weather normalisation

When energy measurement data, monitored during different periods or heating seasons, have to be compared, the influence of different outdoor conditions should be filtered out. A normalisation commonly done is dividing the measured energy use by the total amount of heating degree days (HDD) during the measurement period. In theory, the heating degree days of a period equal the sum of all the daily differences between in- and outdoor temperature that remain after the potential temperature rise due to solar and internal gains, and that should be compensated by the heating system:

$$HDD = \sum_{d=1}^{N} (T_{i,ref} - T_e) \tag{2.1}$$

T_e is the daily external temperature and $T_{i,ref}$ the daily reference indoor temperature, defined as $T_{i,ref} = T_{i,set} - \Delta T_i$ with $T_{i,set}$ the indoor set temperature and ΔT_i the temperature rise due to solar and internal gains (Hong et al. 2006). If the external temperature rises above a preset value above which no heating is required (e.g. 12 °C), the heating degree day for that day is zero.

The previous definition of HDD implies the knowledge of both $T_{i,set}$ and ΔT_i. Since both are highly dependent on detailed occupant and dwelling information that is often unavailable, $T_{i,ref}$ is frequently taken as a constant value for all dwellings, e.g. 15 °C. Additionally, the amount of heating degree days is now independent from the type of dwelling or inhabitant, making it a representative figure for the outdoor climate only. However, by doing so, the differences in external temperature are indeed accounted for, but there is no coverage anymore for differences in solar radiation.

Data filtering

When the refurbishments only concern the building envelope and/or the space heating system, one is typically interested in the effect of the refurbishment on the energy use for space heating only. When hot tapwater and space heating depend on the same fuel source, their energy use is 'bundled' in the same meter reading. To filter out the energy use for hot tapwater, an estimate of the latter needs to be done. This is a difficult task, as it is largely based on the researcher's own expertise and a variety of assumptions. Large errors could thus be induced in the remaining 'measured' energy use values.

Also, many households use more than one heating system and vary between e.g. the central heating system on gas, an electric convector in the bathroom, a wood stove in the living room etc. As this information might be spread over different fuel bills, it might stay under the radar for the researchers.

2.2.2 Predicting energy savings

Predicting energy savings is typically done by engineering estimates of energy use before and after refurbishment. It is important to acknowledge the huge spread in possible estimates. As stated by Sanders and Phillipson (2006), '*the predictions depend on the quality of the model, not on some essentially unknowable 'right answer'* '. There is a wide range of predictive models available, ranging from simplified to very complex. The complexity of the predictive models often depends on the amount of detail of the input parameters available. Many detailed models, like those based on the standard ISO/FDIS 13790 (2008), are difficult to apply for a large building stock due to the increase of computer simulation time and the lack of detailed data. Conversely, simplified models can be used for a larger number of buildings, but inevitably induce some minimal errors (Cayre et al. 2011).

No further detail on modelling issues will be given here, as most part of this work is dealing with how the modelling process should be adapted to obtain more reliable predictions. For now, it is important to stress that evaluations of energy efficiency programs should clearly describe and explain the predictive models used. If not, it is difficult to compare different shortfall outcomes of different energy efficiency schemes.

2.3 Empirical evidence

Much literature and many literature reviews can be found on evaluating the effects of energy efficiency programs in the residential sector. Yet, the variety amongst them is huge: in the quality of the measurement data, the scale and sample size of the project, the evaluation parameters, the data analysis method used, the predictive models used, the transparency and clarity in the reporting etc. In this overview, only those studies are selected that offer reasonable insight in the methodologies and metrics used.

Hirst et al. (1989)

The Hood River Conservation Project offers one of the earliest insights in the efficiency of residential retrofit programmes. All dwellings in this programme were electrically heated. Engineering-based estimates predicted an electricity saving of 6.1 MWh per household due to the program. However, actual electricity use was only cut by an average of 2.6 MWh per household per year (14 % of initial use) between 1982/83 (pre-retrofit) and 1985/86 (post-retrofit), leading to a shortfall value of almost 60 %.

This rather high value must be seen within the specific time context of the programme. Even before the project began and stimulated by the 40 % increase in real electricity prices after the second oil crisis in 1979, households had adopted many conservation actions (especially use of wood for space heating instead of electricity). These low initial energy use levels are in contrast with the rather high levels of the post-retrofit period, coinciding with the slow revival of the economic climate and the favorable energy prices. The combination of both effects could indeed easily lead to much lower energy savings than expected.

Bell and Lowe (2000)

In the study of Bell and Lowe (2000), good monitoring data were available for 21 experimental houses and 11 control houses in the UK. The 21 experimental houses were insulated with 200 mm loft insulation, blow-in fibre cavity wall insulation and draught-proofing to existing windows and doors. A new central heating system with condensing gas boiler was installed, together with a ventilation system. The recorded gas energy use in the control group (where no renovation occurred) was higher than in the retrofitted group, but the difference was only one half of the calculated difference, suggesting a shortfall of 50 %. Unfortunately, the authors do not elaborate on how the energy modelling predictions have been done.

Haas and Biermayr (2000)

Although there are some major weaknesses in the analysis of Haas and Biermayr (2000), the study is nevertheless mentioned here since it is commonly cited and still contains some interesting parts. The authors use 5 different approaches to assess the size of what they call the *rebound effect*. In practice however, they make no distinction between shortfall and rebound effect, implicitly assuming that any shortfall observed, is entirely attributed to the rebound effect. As already explained before, this is not correct.

Only one of their 5 approaches is mentioned here, as it does offer a methodologically robust estimate of the shortfall. The energy savings for space heating for 12 large multi-family dwellings in Austria are investigated and compared with the calculated energy savings. The average energy saving is estimated as 58 kWh/(m^2.a), while the actual energy savings were only 41 kWh/(m^2.a). Thus, a shortfall value of 30 % is observed.

Henderson et al. (2003)

On behalf of the Energy Saving Trust in the UK, Henderson et al. (2003) performed an analysis on the meter readings of almost 8000 electrically heated dwellings, before and after receiving different insulation upgrades. The average measured annual saving was 1383 kWh/household/year (normalised and corrected for outdoor weather conditions). The expected savings were calculated using BREDEM v12 (Building Research Establishment 1997), a method consistent with the European Standard (ISO/FDIS 13790 2008) and widely used in the UK. Savings for particular measures were calculated from a standard case typical of each house type rather than from audits of individual dwellings, which would have added considerably to cost. Energy savings were predicted as 4356 kWh/household/year, leading to an average shortfall of 68 %.

Additionally, the richness of the data allowed some in depth analysis of the observed shortfall. Figure 2.2 shows the shortfall (called the 'comfort factor' by the authors) for two dwelling types, plotted against the ratio of measured relative to calculated energy use prior to the retrofit. The more the prior energy use is overestimated, the higher the shortfall. This is not at all surprising as dwellings who initially consume only 20 % of the expected amount of energy, cannot save the energy they are not actually using. It also indicates the impact of poor heating in poorly insulated dwellings. As the energy models like BREDEM assume adequate levels of heating (21 °C in living area; 18 °C elsewhere), the dwellings with low ratios of actual over calculated energy use, are very likely to heat their home to rather low comfort levels. After retrofit, they are expected to take back a large amount of the energy savings into an increased comfort, explaining the higher shortfall values.

BRE Client Report 16099 (2003)

This client report, prepared by BRE, is not publicly available, but the results can be obtained via the review of Sanders and Phillipson (2006). A large retrofitting programme was set up in 91 electrically heated homes in the UK and the energy savings were observed via both internal temperature and

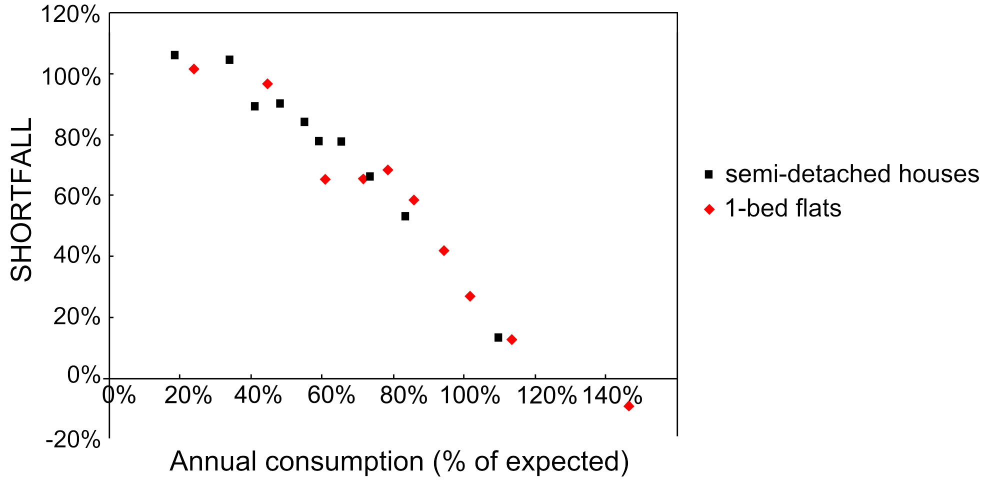


Figure 2.2: Observed shortfall for semi-detached houses and flats against prior measured energy energy use, expressed in percentage of its expected prior energy use. Source: Henderson et al. (2003).

energy use monitoring. The calculated energy savings were based on BREDEM, but with implementation of the internal temperatures as measured during the campaign. It is thus believed that the energy saving estimates are more accurate than when a standard heating level is assumed. Still, a remarkably high shortfall value of 53 % was found.

Henderson (2004)

Again on behalf of the Energy Saving Trust (UK), Henderson (2004) performed a large scale analysis on 3 datasets, containing the monitored energy savings of in total 1632 gas heated homes receiving cavity and wall insulation measures. The analyses carried out were very similar to those reported for electrically heated houses in Henderson et al. (2003) (see above).

Two slightly different calculation schemes were used to assess the predicted energy savings (both based on BREDEM). The first one resulted in shortfall values of 52 %, 49 % and 51 % for the 3 datasets respectively, or a weighted mean of 51 %. The second one gave 60 %, 57 % and 60 % respectively and a weighted mean of 59 %. The different schemes highlight how any shortfall value indeed depends on the calculation method used to estimate the energy savings. Similarly as in Henderson et al. (2003), it was observed that the shortfall declined as prior energy use increased. Also, no statistically significant difference in shortfall was observed between either cavity or wall insulation.

Martin and Watson (2006)

A large scale monitoring project was set out by Martin and Watson (2006). The energy use and indoor temperatures were monitored in 59 dwellings across England receiving insulation upgrades (cavity wall and loft insulation). The monitoring was done both 12 weeks before and 12 weeks after retrofit. For a subset of 25 dwellings, energy use predictions were performed with BREDEM v8 (Building Research Establishment 1997), making use of the actual measured outdoor temperatures. A drop in energy use from 2224 kWh/day to 1475 kWh/day was predicted, or 749 kWh/day savings. In reality, the energy use dropped from 1924 kWh/day to 1477 kWh/day after retrofit, only 447 kWh/day saved. A shortfall value of 40 % is then obtained.

In this study, almost all shortfall is to be attributed to the incorrect estimate of the pre-retrofit use. Although this estimate is wrong by a relatively small amount ((2224 − 1924)/2224 = 13 %), it still leads to energy savings that are hardly half of what was expected. Hence, this study clearly illustrates the importance of estimating the pre-retrofit use as accurately as possible.

Warm Front energy efficiency scheme in the UK (2006)

In the UK, a major government funded domestic energy efficiency scheme, called *Warm Front* (Hong et al. 2009, 2006, Oreszczyn et al. 2006), consisted of providing grants for the installation of cavity wall insulation, loft insulation, draught proofing and, in some cases, the option of gas wall convector heaters or a gas central heating system. Based on detailed monitoring data on indoor temperature and fuel use, a longitudinal comparison could be made for 390 households. Weather normalisation was carried out by using heating degree days based on the measured internal temperature $T_{i,set}$ (see Equation 2.1).

The modelled and normalized fuel use for space heating was obtained as follows:

$$E_{norm,pred} = \frac{24(U_m A_T + 0.33 n_{inf} V_i)}{\eta_{heat} A_{floor}} \qquad [\text{Wh/(m}^2\text{ K day)}] \tag{2.2}$$

with U_m and A_T respectively the dwelling mean thermal transmittance [W/(m^{2}K)] and heat loss area [m^2], n_{inf} the background air infiltration rate [1/h], V_i the internal dwelling volume [m^3], η_{heat} the total heating efficiency [-] and A_{floor} the floor area [m^2].

The comparison of the normalised measured and calculated energy use use is shown in Figure 2.3. Although a theoretical energy decrease of 25-35 % is predicted after the *Warm Front* improvements (Figure 2.3A), no statistically significant difference in pre- and post-intervention distributions is found in the measured data (Figure 2.3B). As no energy savings are achieved, this would correspond with a shortfall of 100 % (ΔE_{meas} = 0, see Equation 1.1 page 3).

This shortfall figure of 100 % is significantly higher than the shortfall values found in the other studies. Its high value is even more remarkable, as the user behaviour component, typically included in the shortfall and thought to make up a considerable part of it, is less considered here due to the use of dwelling and inhabitant specific heating degree days, which are in addition different before and after retrofit. The discrepancy between the normalised monitored and modelled results is thus, in theory, to be attributed to purely dwelling dependent parameters. The authors indeed mention increased air infiltration rates due to the installation of a gas central heating system (the pipe work was laid through the suspended floor boards) and incomplete insulation filling of exterior wall and loft spaces depicted by infrared thermography. However, it might as well mean that the data processing should be questioned. The authors mention the possibility that the normalised monitored space heating energy use is too sensitive to the degree day calculation and that the theoretical model for predicting the energy use is too simplistic. As such, despite the richness of the gathered data, the

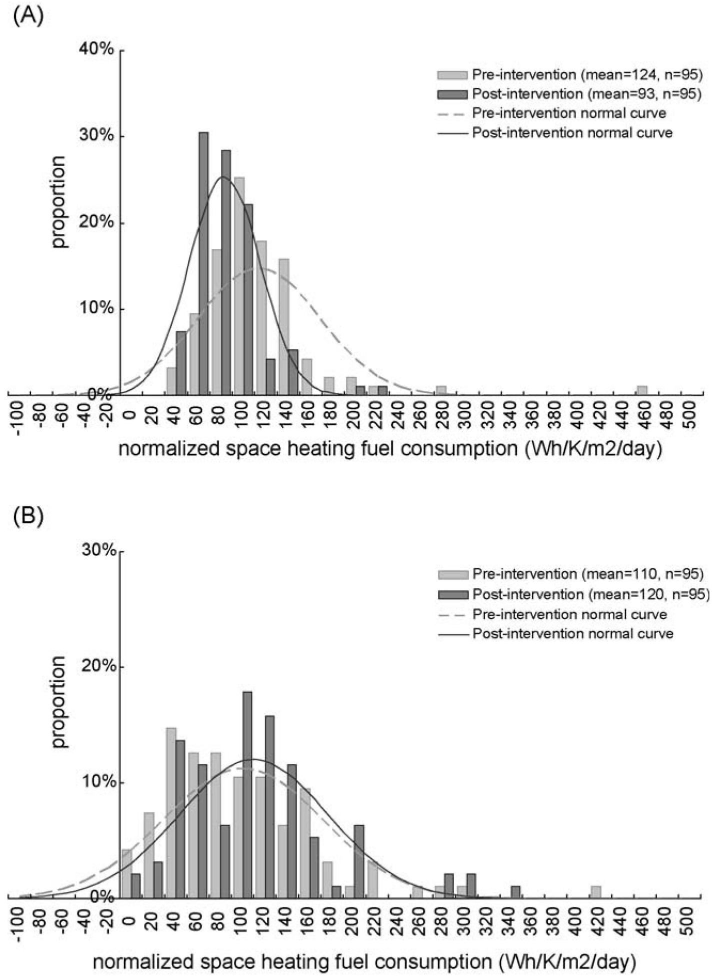


Figure 2.3: Comparison of longitudinal normalised space heating energy use between pre- and post-intervention dwellings. (A) Modelled and (B) Monitored. Source: Hong et al. (2006).

different analysis method used in this study makes it difficult to compare this shortfall estimate with the other studies.

Hens (2010b)

The study of Hens (2010b) discusses the stepwise retrofit of a Belgian semi-terraced house over a timespan of almost 30 years. The mean energy saving for space heating was predicted to be 44.7 MWh/year over the total timespan. In reality only 32 MWh per year was saved, or, a shortfall of 28 %. Main reasons are sought in "*(i) only part of the dwelling being heated, in contrary to the assumption of the whole volume being heated in the calculations, (ii) a heating system efficiency decreasing with part loading and (iii) differences in the solar coefficient among successive years*".

Rogan and Gallachóir (2011)

A large evaluation study of residential building regulations for new dwellings in Ireland has been performed by Rogan and Gallachóir (2011). They compared the energy use of a large control group (semi-detached dwellings in Dublin built to 1997 Building Regulations) with the energy use of a large treatment group (semi-detached dwellings in Dublin dwellings built to the 2002 Building Regulations). The 2002 Building Regulations succeeded the 1997 Building Regulations and contained U-values which should have provided in a 20 % reduction in dwelling energy use. Applied to the empirical baseline energy use of the control group (13.43 MWh per dwelling per year), this means a target saving of 2.68 MWh per dwelling per year. An independent sample T-test was performed on the filtered and normalised data of both groups, showing a mean saving, with 95 % confidence, of only 1.35 MWh±20.3 % per dwelling per year (reduction of 10.1 %). Or, the shortfall in this study equals 50 %.

Summary of empirical evidence

The previous shortfall estimates are summarized in Table 2.1. The variety is large, with values ranging from 28 to 68 %. Also, a lot depends on the calculation method used: different calculation tools can easily lead to different shortfall values. Nevertheless, an overall value of 50 % seems to be a good indicator value of typical shortfall in residential renovation projects.

Table 2.1: Overview of shortfall estimates in residential retrofitting projects.

Authors	*Country*	*n*	*Shortfall* [%]	*Comments*
Longitudinal study				
Hirst et al. (1989)	US	320	57	Electrically heated dwellings; results must be seen in context of after 1979 oil crisis
Haas and Biermayr (2000)	AT	12	30	12 multi-family houses
Henderson et al. (2003)	UK	8000	68	Electrically heated dwellings; higher shortfalls for lower initial energy uses
BRE Client Report (2003)	UK	91	53	Calculated savings based on measured indoor temperatures
Henderson (2004)	UK	1632	51 / 59	Two calculation schemes
Martin and Watson (2006)	UK	25	40	All shortfall to be attributed to bad pre-retrofit estimate
Hong et al. (2006)	UK	390	(100)	Results sensitive to heating degree days normalisation procedure
Hens et al. (2010)	BE	1	28	
Cross-sectional study				
Bell and Lowe (2000)	UK	21	50	
Rogan and Gallachóir (2011)	IE	>139000	50	

2.4 Factors explaining the shortfall

In the introduction of this work, the possible reasons for shortfall have been pointed out briefly and the global shortfall framework has been set. A more elaborated discussion on each of the different reasons will be given in the following subsections. They are structured following the schematic representation of Figure 1.5 on page 7: the rebound effect (and related topics), technical issues and the energy performance gap.

2.4.1 Rebound effect and related topics

The inhabitants are commonly cited as a primary cause for disappointing results of energy efficiency programmes. Mostly because it is believed they have changed their behaviour after retrofit. The *rebound effect* is the best-known illustration and will be handled first. As the rebound is strongly linked with the *temperature takeback*, the latter is discussed in this section as well. Finally, although less often mentioned, an *increased window opening behaviour* after retrofit is another possible factor.

The rebound effect

As already mentioned in the introduction of this work (see Section 1.2), the rebound effect (Herring and Roy 2007, Greening et al. 2000, Sorrell and Dimitropoulos 2008, Sorrell 2009, Galvin 2014a) is commonly cited when trying to explain the shortfall in residential energy efficiency programmes.

The mechanism behind this rebound effect is purely economic and can be explained as follows: "*Since energy-efficiency improvements reduce the marginal cost of energy services, the consumption of those services may be expected to increase. This increased consumption of energy services may be expected to offset some or all of the predicted reduction in energy consumption*" (Sorrell 2009). In the context of the residential sector, the reduced cost for space heating after an insulation measure might lead the inhabitants to increase their comfort demand by raising the set temperature and/or heating more rooms more often. A new boiler with higher efficiency might lead to more and longer showers and the purchase of more energy efficient appliances might lead to more frequent use of them. In other words, the theoretical energy savings of certain measures are not achieved due to the inhabitants taking back part of the possible energy saving as an increased comfort level.

The total rebound effect goes beyond the above *direct rebound effect*. For example, the money saved on space heating energy use may be spent on other goods and services that also require energy to provide, like a far-away fly holiday, leading to *indirect rebound effects* (Sorrell 2009). In addition, the rebound effect also includes *economy wide effects*, in which "*a fall in the real price of energy services may reduce the price of intermediate and final goods throughout the economy, leading to a series of price and quantity adjustments, with energy-intensive goods and sectors likely to gain at the expense of less energy-intensive ones*"(Sorrell and Dimitropoulos 2008). In most cases however, only the direct rebound effect is considered.

Even though the mechanism behind the (direct) rebound effect is easily explained, it is far more challenging to estimate its magnitude and importance. All depends on the definitions used, the methodological approaches and data sources available (Sorrell and Dimitropoulos 2008).

A common approach is based on the econometric analysis of large data sources. Such econometric studies typically estimate efficiency and price elasticities. An elasticity of, for example, -0.73

must be seen as the -0.73 % percentage change of the independent variable (e.g. energy demand for space heating) due to a 1 % percentage change of the dependent variable (e.g. heating energy efficiency or energy price). The 'engineering' definition of the direct rebound effect typically relies on the energy efficiency elasticity, while the more common definition in the economic literature estimates the direct rebound as a price elasticity (Sorrell and Dimitropoulos 2008). Based on the econometric evidence collected, Sorrell (2009) suggests a mean value for the direct rebound effect for household heating of around 20 %; Greening et al. (2000) reviewed 26 studies and found rebound effects of 10-30 % for space heating; Haas and Biermayr (2000) conducted an econometric cross-section analysis, leading to an estimated rebound effect of 32 %. These figures should be read as: if the energy efficiency improves by 10 %, the energy use is expected to raise by 10 to 30 %. Or, due to the inhabitants changing their behaviour after retrofit, any technological improvement will only be between 70 and 90 % effective in reducing energy use for space heating.

Temperature takeback[1]

The rebound effect is mostly translated by higher indoor set temperatures or more rooms being heated more frequently. All this leads to an indoor temperature rise, typically referred by as the *temperature takeback* (Deurinck et al. 2012, Dinan and Trumble 1989, Schwarz and Taylor 1995). Small increases in indoor temperatures, in the range of +[0.5-1.5]°C, have indeed been observed in several retrofit monitoring projects (Dinan and Trumble 1989, Henderson et al. 2003, Martin and Watson 2006, Oreszczyn et al. 2006). However, an indoor temperature rise cannot be solely attributed to the inhabitants behaving differently before and after the retrofit. Apart from the *behavioural* aspect, there is also a *physical* aspect (Deurinck et al. 2012). When improving the insulation quality of the building envelope, the transmission and infiltration heat losses decrease, not only in the heated zones but also in the unheated zones. Under equal thermostat settings, this leads to less energy demand in the heated zones and higher temperatures in the unheated zones. A better insulation and air-tightness level also leads to smaller temperature drops between two heating periods. As a result, both dwelling and time averaged indoor temperatures increase after improvement of the insulation level, even if the inhabitants do not alter their heating pattern. When this temperature rise is not accounted for in the calculations, the post-retrofit net energy demand might be underestimated, thereby attributing to shortfall.

The physical aspect of the temperature takeback has been mentioned by different authors (Sanders and Phillipson 2006, Milne and Boardman 2000, Sorrell et al. 2009) but none of them gives an estimate of the possible impact of these physical processes on the indoor temperature. The latter is done by the author of this work in Deurinck et al. (2012), by means of dynamic building energy simulations. The procedure of Deurinck et al. (2012) is duplicated hereunder, but the results are up-

[1] The content of this paragraph is mainly based on the journal paper "*Assessment of the physical part of the temperature takeback for residential retrofits*" (Deurinck, M., Saelens, D., and Roels, S. (2012). *Energy and Buildings*, 52:112-121.)

dated by using the probabilistic behavioural model and two-zone building model from the following Chapters 3 and 4.

Procedure The 10 real dwellings and the 21 fictive dwellings from Chapter 4 are modelled in the dynamic building simulation software package `TRNSYS 17`. The implemented heating behaviour (Chapter 3) is conceived as realistic as possible by basing it on typical *zonal heating* (frequently heated dayzone and less frequently heated nightzone) and *intermittent heating* (different time schedules in both zones). By doing so, the physical processes behind the temperature takeback (higher temperatures in less heated zones and smaller temperature drops) are allowed for. A set of 200 stochastically defined heating profiles is then generated and each of them is imposed to every dwelling variant, leading to a probabilistic outcome per dwelling.

Results Figure 2.4 reveals the physical aspect of the temperature takeback: even though all dwellings undergo the same heating behaviour, the indoor temperature increases with improved insulation quality. The comparison is made with the indoor temperature as assumed in the Belgian energy performance assessment tool (EPR 2010): the whole dwelling continuously heated at 18 °C, thereby ignoring the existence of (physical) temperature takeback. Figure 2.4 confirms how the latter is not the right way to go. Whatever the value chosen for a fixed indoor temperature for all insulation levels, it will be either too high for the poorly insulated dwellings or too low for the highly insulated dwellings.

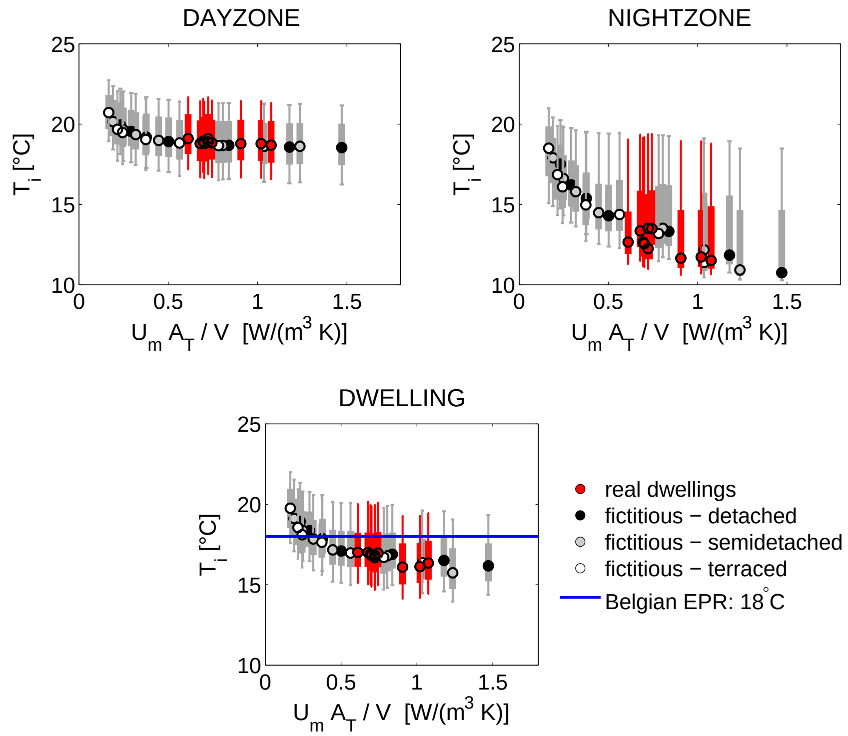


Figure 2.4: Indoor temperature at T_e = 5 °C as a function of specific transmission heat losses ($U_m A_T$ [W/K]) per m^3 heated volume (V [m^3]): for the probabilistic behavioural model of Chapter 3 (marker = median ; box = 25th until 75th percentile; whiskers = 10th until 90th percentile) and for the default assumption in the Belgian energy performance assessment method (blue line).

The impact on the net energy demand for space heating (no incorporation of heating system efficiencies) is given in Figure 2.5. As expected, with the 18 °C being an overestimation of the indoor temperature of poorly insulated dwellings, it is no surprise also the energy demand is overestimated. All of course depends on who is to inhabit these dwellings, but overall, the impact of not incorporating zonal and intermittent heating is likely to overestimate their pre-retrofit energy demand by 10 to 20 %. When retrofitting them, the indoor temperature automatically rises and closely approaches the 18 °C. Consequently, the error in net energy demand is smaller after retrofit.

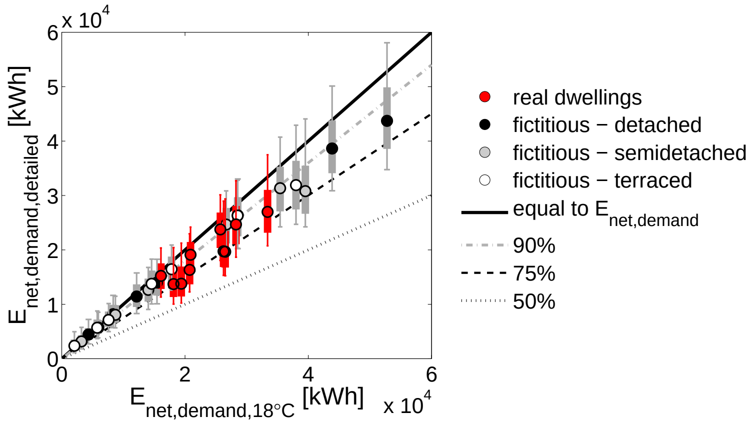


Figure 2.5: Heating season net energy demand for space heating for the probabilistic behavioural model of Chapter 3 ($E_{net,demand,detailed}$; marker = median ; box = 25th until 75th percentile; whiskers = 10th until 90th percentile) against the mean outcome when continuous heating at 18 °C is applied ($E_{net,demand,18\,°C}$; with all other parameters from the behavioural model unaltered).

Conclusion If indoor temperatures rise after retrofit, the inhabitants should not be directly 'blamed' for taking back part of the energy savings in a comfort enhancement. Dynamic building simulations clearly show how the indoor temperature inevitably rises after retrofit - even if identical heating behaviour is maintained. This physical part of the temperature takeback should be incorporated in a reliable energy saving prediction. Fortunately, when using a more realistic behavioural model including zonal and intermittent heating, as will be done in this research work, this physical takeback will be automatically accounted for.

Increased opening of windows after retrofit

An increased amount of window opening after retrofit is suggested by a limited number of a studies as a plausible explanation for lower energy savings than expected (BRE Client Report 16099 2003, Hong et al. 2006, Summerfield et al. 2007). The idea is that, as typical internal conditions during the heating season become more comfortable for occupants, insulation measures may lead to increased ventilation through increased opening of windows to 'dump heat' (Sanders and Phillipson 2006). A comparison of average window opening days based on the household survey in Hong et al. (2006) showed that a centrally heated dwelling is likely to open windows on average 3.3 days per week compared to 2.9 days in a non-centrally heated dwelling, indicating that the installation of a central heating system may also result in increased occupant venting through a feeling of overheating/stuffiness.

Yet, no measurement campaigns were found in which the window opening behaviour was explicitly monitored both before and after retrofit. Also, the insulation level of a dwelling is not recognized as influential driver of occupants' window opening behaviour (Fabi et al. 2012). Until more empirical evidence can be found, increased window opening as possible explanation for shortfall will remain a hypothesis.

2.4.2 Technical issues/shortcomings

While the previous section focused on the inhabitants, the present section looks closer into the (unexpected) technical issues that can arise when retrofitting dwellings.

In-situ versus theoretical performance

Shortfall can be attributed to renovation measures not performing as technically expected. Performance predictions in general tend to be based upon an assumption of ideal behaviour of materials and products under standard conditions, combined with perfect installation. It is therefore perhaps not surprising that in reality performance rarely matches expectations (Stafford et al. 2011). A small selection of the many empirical evidence is given hereunder.

Measurements on insulated cavity walls showed how poor execution quality leads to a severe drop in thermal resistance of 4.5m^{2}K/W (good execution) to 0.8m^{2}K/W (bad execution) (Hens 1998). The reason was the occurrence of buoyancy driven air loops around the carelessly placed insulation panels, leading to the short circuit of the insulation.

In the Warm Front study project (Hong et al. 2006) a limited number of post-intervention properties were inspected by infrared camera showing that for properties that had their cavity walls insulated, an average of 20 % of the cavity wall area was missing insulation. Similarly, 13 % of the loft area that could be theoretically insulated, had missing insulation. Also, the theoretical reduction in air infiltration due to draught stripping was not observed because the installation of a gas central heating system, a measure not normally associated with ventilation, was found to increase the air infiltration rate by 13 % due to the unsealed piping work through the suspended floor (Hong et al. 2004).

Following a research project on newly built dwellings, Wingfield et al. (2009) found that the measured system efficiencies of the installed gas-fired heating systems in occupied dwellings were less than expected and that measured boiler efficiencies fell below the declared theoretical ratings.

In the monitoring campaign of Bell et al. (2010) on newly-built low carbon houses in the UK, a large discrepancy was observed between predicted (127 W/K) and measured (196 W/K = +54 % of predicted value) building envelope heat loss. This discrepancy was believed to be "*the result of design and construction process factors that (i) underestimated the amount of timber in the walls and roof (23 % of the difference), (ii) did not account fully for thermal bridging at junctions and openings* *etc. (25 %), (iii) did not account for heat loss via a thermal bypass within the party walls (30 %) and (iv) did not maintain window performance when a change of supplier occurred (21 %)*". Also, the in-situ airtightness levels were about 50 % lower than initially estimated and the communal ground source heat pump did not achieve its expected performance.

Even this limited selection of studies shows how in-situ values of U-values, efficiencies, airtightness levels etc. can strongly deviate from theoretically assumed values. Poor workmanship is a possible explanation, but even if attention is put in an accurate installation by well-trained craftsmen, differences between the in-situ and theoretical performance are still observed (Stafford et al. 2011).

Drop in production efficiency of the boiler

A traditional non-modulating on/off boiler attains it highest efficiency when it is able to operate at full load, preferably during long, uninterrupted periods. When installed in a poorly insulated dwelling, this condition is fairly easily fulfilled. However, when the dwelling's building envelope is insulated while maintaining the existing boiler, the heating demand of the dwelling is reduced and the boiler becomes increasingly oversized, leading to a severe drop in both production and system efficiency (Peeters et al. 2008, Lazzarin 2014). An illustration of this is given in Figure 2.6. Following dynamic building energy simulations, the monthly production efficiencies prove to be dependent both of the insulation quality of the dwelling and outdoor weather conditions (~ month of the year). Highest production efficiencies are found in winter and for the least insulated dwelling (although it already performs well with an average U-value of only 0.5 W/(m^{2}K)). The efficiencies clearly drop when moving towards summer and for the best insulated dwelling (U = 0.2 W/(m^{2}K)). Although not shown here, more figures are found in Peeters et al. (2008) for the overall efficiency of the heating system (including both production, distribution, emission and control).

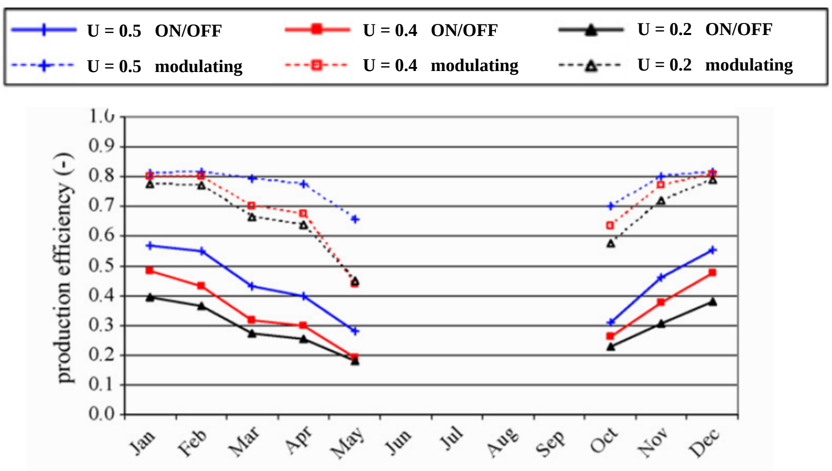


Figure 2.6: Monthly production efficiencies, following from dynamic building energy simulations of a compact terraced house in 3 insulation levels (U = 0.5 - 0.4 - 0.2 W/(m^{2}K)), equipped with thermostatic radiator valves and an ON/OFF or modulating high efficiency boiler. Source: Peeters et al. (2008)

The above can also be expressed as a function of the ratio of (monthly) heat gains over heat losses, shortly called the heat balance ratio (Peeters et al. 2008, Parys 2013). Low heat balance ratios are typically found in poorly insulated dwelling and/or during winter period and yield the highest efficiencies. High ratios, found in well insulated dwellings and/or during spring/autumn, are associated with low efficiencies. So, to capture the post-retrofit efficiency drop when estimating energy savings, one could rely on regression curves that express the efficiency as a function of the heat balance ratio (see further in Chapter 4).

In-/decreased airtightness

Retrofit measures such as installing new window frames and insulating the pitched roof are often evaluated based on their decrease in transmission losses. However, they often also lead to lower infiltration losses: the new window frames are more airtight than the original ones and after insulating the pitched roof, an airtight vapour layer needs to be added to decrease the condensation risk. The overall airtightness of the dwelling envelope decreases, so often (extra) ventilation will be necessary to maintain a good indoor air quality. This counteracting effect (less transmission and infiltration losses but more ventilation losses) is rarely incorporated when calculating the energy savings.

A limited number of studies is available in which the reduction in air infiltration rate has been measured for several common renovation measures. The Warm Front Study group Hong et al. (2004) performed fan-pressurization tests in 191 dwellings in England, of which a part had undergone a combination of retrofit measures (cavity wall or loft insulation, draught stripping or renewed gas central heating system). When the cases receiving a new central heating system were excluded from the analysis (the installation of the unsealed plumbing cancelled out part of the airtightness improvement), a drop in average air infiltration rate of 14 % was observed.

In the work of Bell and Lowe (2000), the airtightness of 2 houses was tested both before and after retrofit, leading to a remarkably large reduction of respectively 61 and 71 %. This was achieved by improved performance of windows and doors, sealing of suspended timber ground floors and the repair of defects in the plaster work around window frames.

Janssens and Delghust (2009) investigated the airtightness of 9 single-family dwellings in Belgium after the air cavity walls had been filled with insulation. A drop in air infiltration rate ranging from 5 to 20 % was found.

Ten houses in the UK which were undergoing a (partial) window replacement, were tested to determine air infiltration rates (Ridley et al. 2006). An average reduction in air infiltration rate of 38 % was found within a total range of [10 - 65] %.

In the framework of this research, additional measurements have been carried out to analyse the effect on the airtightness of two commonly executed renovation measures in Belgium: the replacement of windows and the insulation of the pitched roof. The latter is included in the analysis, because it mostly implies the application of an airtight vapour barrier, leading to an enhanced airtightness as a positive side-effect. The results are summarized in Table 2.2.

Table 2.2: Air infiltration testing results[a] on Belgian single-family dwellings undergoing either window replacement or a pitched roof insulation.

	V_i [m^3]	A_T [m^2]	incl. attic?	$n_{50,before}$ [h^{-1}]	$n_{50,after}$ [h^{-1}]	Percentage reduction [%]
				replacement of windows		
1	311	339	-	7.9	4.9	37
2	298	284	-	10.0	4.4	56
3	333	317	-	6.4	5.0	21
4	247	309	-	5.3	2.3	56
5	247	309	-	4.5	2.7	41
6	281	263	-	4.9	3.8	22
7	156	219	-	5.8	3.9	32
8	1100	795	-	6.5	4.7	28
				insulation of pitched roofs		
9	1100	795	-	4.7	3.4	29
10	434	431	-	5.7	5.8	0
11	298	419	-	22.6	17.8	21
12	439	379	-	6.1	6.0	2
13	370	431	-	11.7	10.9	7
14	333	317	-	5.9	6.4	-8
15	623	495	x	25.6	7.3	71
16	379	335	x	16.8	8.3	51
17	277	290	x	19.8	11.4	42
18	411	419	x	18.6	7.7	59
19	763	507	x	30.5	4.5	85

[a] The results have been obtained in collaboration with two Master students and have not been published yet, apart from their Master thesis (see Claeys and Yun Huang (2012)).

The *window replacement* resulted in a mean n_{50} reduction of 37 % within a total range of [21 - 56] %, which is in remarkable agreement with the above findings of Ridley et al. (2006). When analysed cross-sectionally, a two-tailed t-test indeed reveals that the mean n_{50} values from the before and after group are significantly different. Linking the measured air flow reduction ($V_i \times (n_{50,before} - n_{50,before})$) with the total replaced window perimeter did not yield any useful relation.

For the *pitched roof insulation*, a distinction must be made whether the total measured volume (= V_i) is included in the attic volume or not. In those 6 cases where the attic volume was not included, the attic volume is mostly separated from the rest of the dwelling by a closed door or a trapdoor. The impact of airtightening the pitched roof then proves to be quite small and highly variable from an increase in n_{50} of 8 % to a decrease of 29 %. This is as expected since the impact can only be indirectly measured via cracks and air leakage paths between attic and dwelling volume. In those 5 cases where the attic volume was in open contact with the rest of the dwelling, it is no surprise that the impact of the retrofit is much higher with n_{50}-reductions ranging from 42 % to 85 %. Unfortunately, the sample size of each of the subgroups is too small to generate more reliable and widely applicable conclusions.

Overall, the previous literature overview and the measurement campaign show how commonly performed retrofit measures have their impact on the overall airtightness of the dwelling, with the observed reductions strongly depending on the type of retrofit measure. Although the drop in infiltration rate is beneficial for the energy use for space heating, it can have an harmful impact on the indoor air quality. So often, these retrofit measures should but not always are accompanied by the installation of a proper ventilation system, in turn leading to higher energy uses for space heating.

Thermal bridging

When insulating existing dwellings, it is not always technically possible (and/or economically feasible) to reduce all thermal bridging. When for example interior insulation is applied, serious thermal bridging can occur at places where the insulation layer is unavoidably interrupted like at the junction of the interior floor slab with the outer wall. Apart from the increased risk of mould growth, this also has consequences for the energy savings. In badly or uninsulated buildings, thermal bridges only have a minor share in the overall transmission heat loss. However, it is well-known that the relative effect of thermal bridges may increase when the thermal resistance of the building envelope is increased (Janssens et al. 2007, Berggren and Wall 2011, Capozzoli et al. 2013). So, while ignoring thermal bridges might be an acceptable simplification in predicting the energy use of the uninsulated dwelling, it could be no longer defendable after retrofitting it to current energy standards[2].

Several studies have presented many different numerical results for different cases (Janssens et al. 2007, Theodosiou and Papadopoulos 2008, Cappelletti et al. 2010, Capozzoli et al. 2013, Berggren and Wall 2013). It is not possible though to give generally applicable values for the relative share of the thermal bridges in the overall transmission heat loss of dwellings. All depends on the measuring system used (internal or external dimensions −Berggren and Wall (2013)), the typology of the dwelling (more compact buildings tend to have higher shares −Janssens et al. (2007)), the insulation level of the building components used (see above), the quality of the detailing, the position of the insulation layer etc. Therefore, the impact of thermal bridges will be illustrated hereunder for a typical small Belgian row house in which interior insulation is applied.

Case study The facade of a small terraced house is chosen (Figure 2.7) in which 5 different thermal bridges occur: 3 window junctions (lintel, sill and reveal), the junction of the outer wall with the wooden beam internal floor (4) and the junction of outer wall with the partition wall (5).

[2] The concept of thermal bridging can as well be considered as a technical issue in shortfall (due to technical constraints, not all thermal bridges can be avoided when retrofitting the building envelope) or as a modelling issue (not incorporating the thermal bridges in the calculations can lead to an incorrect estimation of the energy savings). For clarity, thermal bridging is only discussed once within this research work, namely here under the technical shortcomings

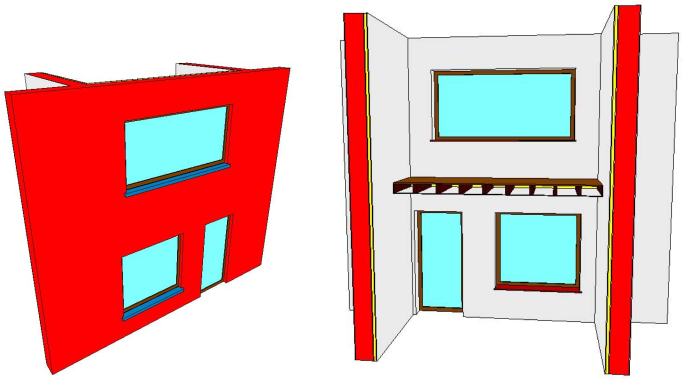


Figure 2.7: Full 3-dimensional model of the case study facade (30 cm massive brick walls, wooden beam internal floor).

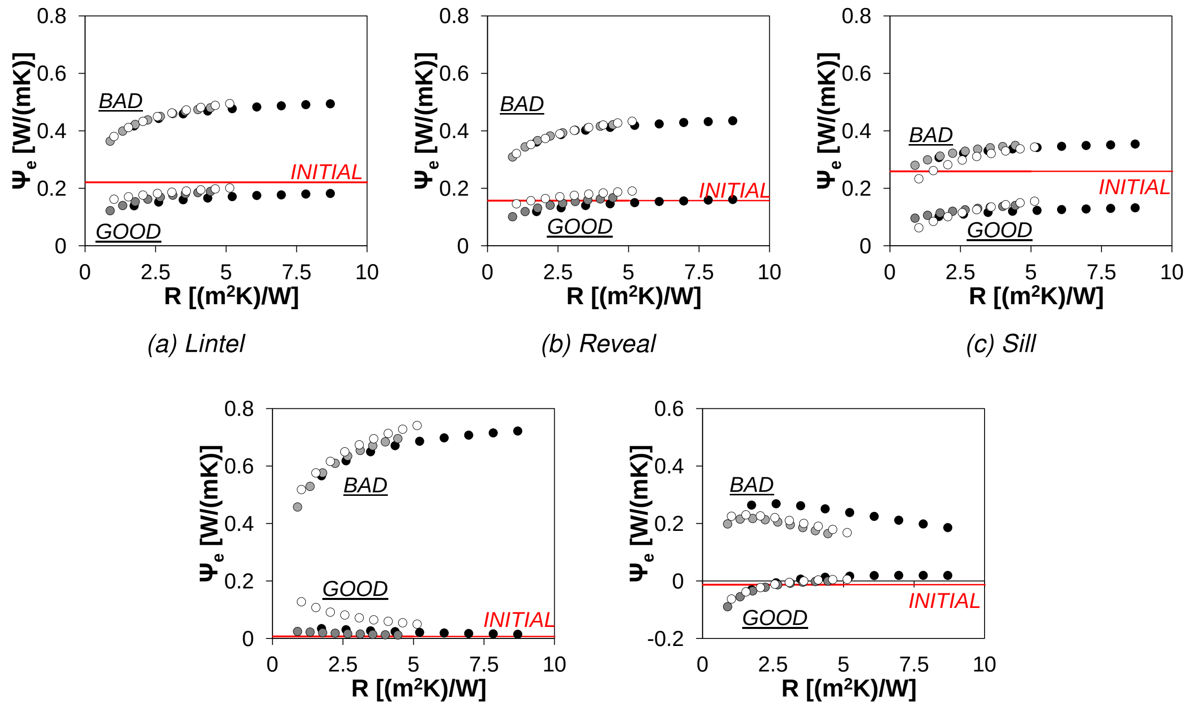
Individual thermal bridges The additional heat loss induced by a thermal bridge, is described by its linear thermal transmittance coefficient, Ψ_e [W/(mK)]:

$$\Psi_e = \frac{\Phi_{2D/3D} - \sum_i (U_i A_i \Delta T)}{L \Delta T} \qquad \text{[W/(mK)]} \tag{2.3}$$

with $\Phi_{2D/3D}$ the total 2- or 3-dimensional heat loss [W], U_i the reference U-value [W/(m^{2}K)] of the building components, A_i the corresponding surfaces [m^2] based on exterior dimensions, ΔT the temperature difference [K] between the interior and exterior environment and L the length [m] of the thermal bridge model. The calculation of $\Phi_{2D/3D}$ is performed in the simulation program `TRISCO` (TRISCO [v12.0w] 2012). This software has been validated in accordance with the international standard EN ISO 10211 (2007).

The Ψ_e-values for 5 individual thermal bridges are given in Figure 2.8 in function of the thermal resistance R of the interior insulation layer, for 3 different insulation materials and for a good and bad detailing level. In the good detailing level, the direct connection between the interior insulation layer and the window profiles is ensured and the interior insulation is continued both between the wooden beams of the internal floor (requiring the local removal of both floor and ceiling) and along the partition walls over a distance of 1 m towards the back facade. In the bad detailing level, neither of the above is done. The initial Ψ_e-values in case of the uninsulated, massive brick wall are shown also (red line).

As expected, most Ψ_e-values rise with increasing thermal resistance. However, they tend to converge to a constant limit value for very high thermal resistances, which is in agreement with Janssens et al. (2007). The difference between bad and good detailing is obvious. While a bad detailing easily leads to Ψ_e-values significantly higher than the initial value, a good detailing is able to strongly reduce the extra heat loss and keep the Ψ_e-value nearly as low as the initial value. Finally, although the insulation material has some minor influence on the calculated Ψ_e-value, the overall picture is rather independent of the insulation material chosen.



(a) Lintel *(b) Reveal* *(c) Sill*

(d) Internal floor *(e) Partition wall*

Figure 2.8: Ψ_e-values of individual thermal bridges as a function of increasing thermal resistance of the interior insulation layer of a massive brick wall for 3 different insulation materials (black: polyurethane board, grey: light-weight autoclaved aerated concrete, white: cellulose) and for a bad and good detailing level.

Impact on transmission heat losses of facade To reveal the impact of thermal bridges on the overall transmission heat losses, two calculation methods are compared, determining the specific transmission heat losses of the facade, $H_{T,facade}$ [W/K]:

(a) No incorporation of thermal bridges: $H_{T,facade} = \sum_i U_i A_i$

(b) All thermal bridges are incorporated by modelling the facade 3-dimensionally/as a whole (see model in Figure 2.7): $H_{T,facade} = H_{T,3D}$

In Table 2.3 the values for $H_{T,facade}$ are given for the original situation and for the situation where an interior insulation layer of 100 mm PUR is applied. For this particular case study, the share of the thermal bridges in the total transmission heat loss of the uninsulated facade remains limited to only 6 %. When 100 mm of PUR is applied, it rises to 51 % under a bad detailing and to 20 % under a good detailing level. This proves how the thermal bridging indeed gains in relative importance when the building envelope is insulated.

However, the overall impact on the overall energy savings should be put in perspective. Even for this compact terraced house –a situation where thermal bridges are expected to be of highest importance compared to other less compact dwelling typologies (Janssens et al. 2007)– the error on the transmission heat loss savings is rather limited. Certainly when effort is put in solving the thermal bridging, the difference between neglecting the thermal bridging and not, is negligible ((60 - 58.8)/60 = 2 %). If bad detailing is adopted however, the transmission energy savings are quite

Table 2.3: $H_{T,facade}$, before and after renovation (100 mm PUR - R = 4.35 m^2K/W)

	BEFORE RENOVATION	*AFTER RENOVATION (100 mm PUR)*		***SAVINGS***
		Bad	*Good*	
	[W/K]	*[W/K]*	*[W/K]*	*[W/K]*
(a) $H_{T,facade} = \sum_i U_i A_i$	71.1	12.3		**58.8**
(b) $H_{T,facade} = H_{T,3D}$	75.3	25.0	15.3	**50.3/60.0**
→ Share of thermal bridges = $\frac{H_{T,3D} - \sum_i U_i A_i}{H_{T,3D}}$	6%	51%	20%	

significantly overestimated ((50.3 - 58.8)/50.3 = -17 %). Given that the transmission heat loss is only a part of the total dwelling heat loss, the actual effect on the energy savings will of course be lower.

Conclusion The well-known principle that thermal bridging becomes relatively more important when shifting towards well and extremely well insulated dwellings is confirmed here again via the above case study. Not incorporating thermal bridging in an energy saving calculation could thus contribute to shortfall, certainly when bad detailing is adopted. Due to the time-intensive procedure to assess their influence however, the effect of (post-retrofit) thermal bridges is only rarely taken into account.

2.4.3 Energy performance gap

As already mentioned in the introduction of this work, shortfall is also due to the inappropriate use of energy labelling tools as energy saving prediction tools. With these tools failing in assessing realistic residential energy uses (called 'the energy performance gap'), it is no surprise they fail in assessing reliable energy savings.

The typical approach for the energy performance assessment tools is briefly discussed first, followed by the empirical evidence for their systematic failure in estimating realistic energy use. Afterwards, possible explanations are given.

Typical approach for energy performance assessment tools

Since the introduction of the European Energy Performance of Buildings Directive (EPBD) in many European countries, national energy performance assessment tools are easily accessible. These tools have mainly been developed to assess and compare the theoretical energy and environmental performance of (newly built) buildings, often via a rather straightforward implementation in a nationally available software program. The energy performance is frequently translated into an energy label (to be used in energy performance certificates), like for example the Standard Assessment Procedure in the UK (SAP 2009), the Energy Performance Rating (EPR) in Germany (EnEV 2009), the E-level in Belgium (EPR 2010). These performance indicators are typically based on estimates of annual energy use for space heating, domestic hot water and ventilation. Other outputs include estimates of the potential for overheating in summer and the resultant cooling load.

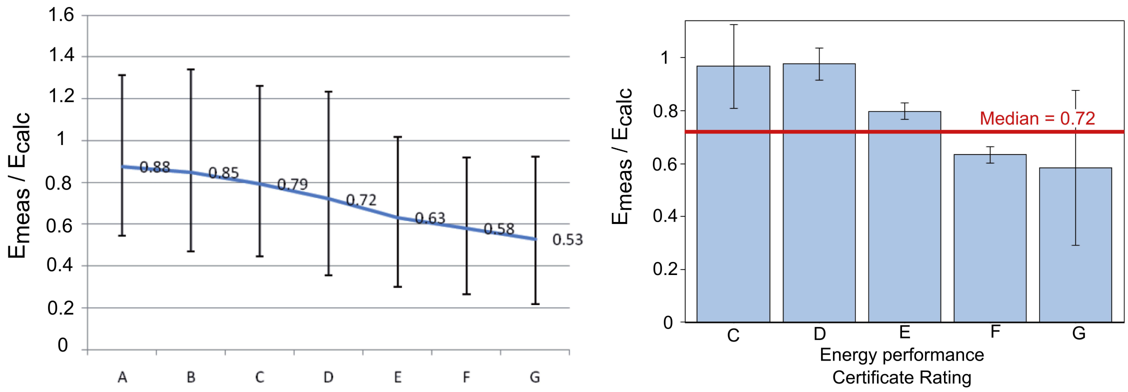
These outputs are mostly generated by means of a monthly steady-state calculation method, predominantly based on (inter)national standards like ISO/FDIS 13790 (2007), EN 832 (2000), DIN V 4108-6 (2003). Typically, the net energy demand for space heating is calculated as the difference between conductive and convective losses and "useful" gains. The latter are the product of the total (internal and solar) gains and a gain utilization factor, which depends on the time constant of the building and the ratio of gains over losses (ISO/FDIS 13790 2007). The monthly net energy demands are then converted to monthly energy uses, using system and production efficiencies. Overall, the dynamic effects are taken into account in a simplified way by introducing correlation factors: the empirically determined gain utilization factor and an adjustment of the set-point temperature regarding the intermittent heating pattern or switch offs (van Dijk et al. 2005, Wauman et al. 2013).

Main input data are the geometry and insulation level of the building envelope and the heating and ventilation system characteristics. As the energy performance should reflect the energetic quality of the building and its systems, independently of any occupants and their behaviours, no input data concerning the inhabitants is required. Instead, a standard dwelling use is implemented by default. Depending on the national context, different settings are used: internal gains as a function of number of occupants or expressed as a function of net floor area (SAP 2009); internal gains as a function of heated volume (EPR 2010); ventilation rates set to default values as a function of heated volume (EPR 2010); the entire dwelling considered to be kept at a fixed indoor temperature (for example 18 °C in EPR (2010) or 19 °C in EnEV (2009)). Typically, the implemented dwelling use reflects an adequate level of heating and sufficiently high air change rates, in order to guarantee a good comfort level and indoor air quality.

Empirical evidence for energy performance gap

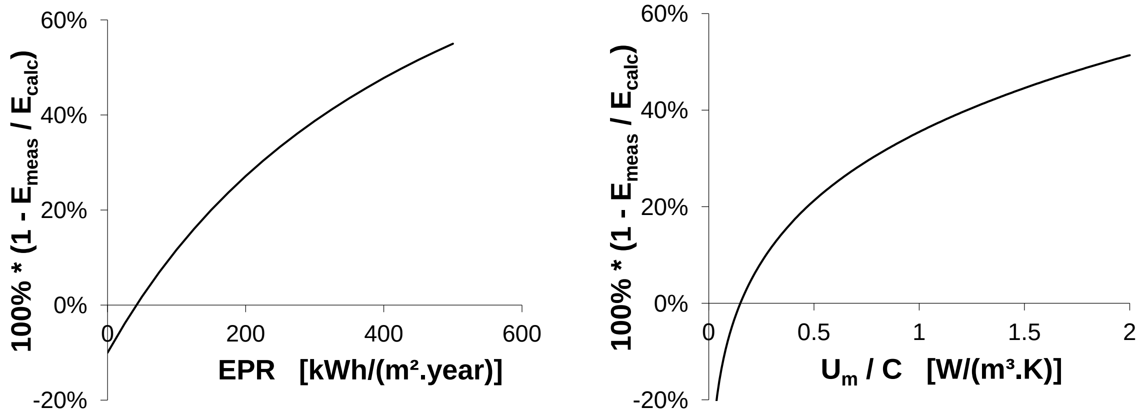
A large amount of academic literature is available about how the above calculation tools, in general, overestimate the actual energy use. It is beyond the scope of this work to give an extensive overview, so we will only discuss the more recent reviewing work. Based on a comprehensive review of eight German studies and four other European studies, Sunikka-Blank and Galvin (2012) found clear evidence of a consistent gap between the calculated and measured energy use. Moreover, they point out how this gap is far from a constant value throughout the building stock: it is higher for poorly insulated, energy-inefficient dwellings. This is illustrated in Figure 2.9 and 2.10 where the respective metrics E_{meas}/E_{calc} and $1-E_{meas}/E_{calc}$ are plotted as a function of the theoretical energy performance.

The performance gap, formulated as $1 - E_{meas}/E_{calc}$ (see Equation 1.2 pg. 6), varies around 50 % for the dwellings with the poorest energy ratings, meaning that the energy labelling tools overestimate their energy use by a factor 2. For the very well insulated dwellings, the opposite is true: E_{meas}/E_{calc} can exceed 1 and $1 - \frac{E_{meas}}{E_{calc}}$ becomes negative, meaning that the tools tend to underestimate the actual energy use. Overall, all curves clearly indicate that, *the worse a dwelling is performing thermally, the more the normative energy labelling methods overestimate the actual energy use*. Sunikka-Blank and Galvin (2012) compared their findings of other comparable studies



(a) The Netherlands *(b) United Kingdom*

Figure 2.9: The ratio E_{meas}/E_{calc} as a function of the EPC rating in (a) the Netherlands and (b) the United Kingdom. Source: Laurent et al. (2013)
(A/C energy-efficient dwelling; G inefficient dwelling; bar = 95 % of the sample)



(a) Modelled on data from Loga et al. (2011) *(b) Modelled on data from Hens et al. (2010)*

Figure 2.10: Regression curves for the energy performance gap ($1 - \frac{E_{meas}}{E_{calc}}$) as a function of the theoretical energy performance for (a) the German context and (b) the Belgian context. Source: Sunikka-Blank and Galvin (2012)

in France (Cayre et al. 2011), the Netherlands (Tigchelaar and Daniëls 2011) and the UK (Kelly 2011) and found similar trends. In addition to the review of Sunikka-Blank and Galvin (2012), Majcen et al. (2013) analysed the relation between the energy labels of almost 200 000 Dutch dwellings and their actual energy use and also observed that less energy-efficient dwellings tend to use less energy than predicted by the labels.

The previous evidence conclusively confirms that **the normative energy labelling tools (i) fail in predicting realistic energy uses and (ii) that the failure is larger for badly performing dwellings**. When predicting energy savings, it is key to at least start from a reliable estimate of the initial energy use of the pre-retrofitted insulated dwelling. Unfortunately, the normative methods fail precisely for these kind of dwellings by largely overestimating their initial energy use. If additionally they tend to underestimate post-retrofit use, it should be no surprise that the (inappropriate) use of these labelling tools plays a major role in the amount of shortfall observed.

Factors explaining the energy performance gap

In fact, many factors that explain shortfall, also explain the performance gap: the discrepancy between actual in-situ and theoretically designed/calculated performance of building components, unexpected/unknown air leakages, not incorporating thermal bridging in the calculations, heating system efficiencies being insulation level dependent, ... These have been discussed before and will not be repeated here.

Additionally, however, there are some major modelling issues, typical for energy labelling tools, that have a large share in the performance gap, and more specifically, in the gap being larger for poorly performing dwellings. They are explicated hereunder.

Modelling of user behaviour Based on the energy performance gap being larger in old, uninsulated dwellings (see above), there is a widely supported consensus that the implementation of standard dwelling use is one of the main reasons why the normative labelling tools fail in predicting realistic energy use (e.g. Hens (2007), Hens et al. (2010), Cayre et al. (2011), Sunikka-Blank and Galvin (2012), Laurent et al. (2013)).

As said, the standard dwelling use typically assumes adequate heating levels and indoor air quality (achieved by sufficiently high air change rates). In newly-built dwellings, built in accordance with the current energy standards, this is indeed a valid assumption. In older, uninsulated dwellings however, it does not hold (see next Chapter 3). Due to a variety of reasons (financial constraints, realistic/personal comfort expectations, inadequate/poor heating systems, ...), the inhabitants (are forced to) apply a minimal comfort level, mostly translated in only heating the main living rooms to an acceptable comfort temperature, and this only at times of presence. Sleeping rooms, hallways, storage rooms, etc. are generally not heated or only kept at a minimum temperature. As a result, actual dwelling mean indoor temperatures can be significantly lower than assumed by the standard dwelling use (e.g. Janssens and Vandepitte (2006)). Also, ventilation systems are most often not present or turned down, causing a significant reduction in actual air change rates. So, in badly performing dwellings, both actual heating and ventilation behaviour lie far from the 'high-comfort' standard dwelling use of the labelling tools.

Also, the importance of modelling the user behaviour correctly cannot be underestimated. As supported by an extensive amount of literature (e.g. Haas et al. (1998), Morley and Hazas (2011), Guerra Santin and Itard (2010), Booth et al. (2011)), user behaviour has shown to have a huge impact on the energy use of a dwelling. In the study of Gill et al. (2010) it is found that behavioural and social factors account for 51 % of the variance in heat use, measured across different dwellings. The detailed analysis of Gram-Hanssen (2010) on different households living in similar buildings shows significant variation in energy use due to different usage patterns of both the house and its heating system. Also, many sensitivity analyses on residential building energy models show how the behavioural factors like the setpoint temperature for heating are found among the most influential parameters (Corrado and Mechri 2009, Brohus et al. 2009, Firth et al. 2010, Cheng and Steemers 2011, Van Gelder 2014).

Given this sensitivity to the user behaviour and the large gap between actual and standard dwelling use, it is clear that a more realistic user behaviour implementation is primordial in assessing more realistic energy use. Hence, the development of a reality-based (probabilistic) behavioural model rightfully earns a great deal of attention in this work and will be handled in the next chapter.

Modelling of infiltration and ventilation rates The heating demand is also sensitive to the convective heat losses through infiltration and (mechanical) ventilation (Corrado and Mechri 2009, Heiselberg et al. 2009, Firth et al. 2010). Estimating them reasonably well is thus important. Unfortunately, the actual air change rates are difficult to model. In reality, very complex air flow schemes can occur, depending on a large number of factors like the ventilation system's configuration, wind shielding conditions, (unknown) air leakage paths, thermal stack, user interaction by window opening, ... (Janssens et al. 2009). Complex modelling tools and detailed input data are thus needed to generate a reliable estimate of actual air flows. Certainly in an energy labelling context, this is unfeasible. Hence, the energy labelling tools often rely on simplified models to assess air flows, thereby possibly inducing large errors on the estimated convective heat losses.

Simplified core calculation method As said, many labelling tools rely on a monthly quasi-steady state calculation method, often based on ISO/FDIS 13790 (2007), using simple algebraic equations and relying on correlation factors, like the gain utilization factor, to incorporate the dynamic effects. One might question if these tools are able to sufficiently capture the complex dynamics of a dwelling.

Both Loga et al. (1999) and Van der Veken et al. (2004) compared the results of quasi-steady state calculations to those of dynamic simulations and found that the predicted net energy demands of both methods were very similar in continuously heated buildings. Under continuous heating regime, the capacitive effects of the building are thus reasonably well captured by the quasi-steady state calculations. For intermittently heated buildings however, the conclusions are different. Many studies found significant discrepancies between static and dynamic methods and indicate the gain utilization factor in the quasi-steady state methods as predominant factor for these discrepancies (Loga et al. 1999, van Dijk et al. 2005, Wauman et al. 2013). Similarly, Corrado and Fabrizio (2006, 2007) and Jokisalo and Kurnitski (2007) reveal the dependency of the gain utilization factor to the specific use and typology of the building.

Given that residential buildings are predominantly heated intermittently, the use of quasi-steady state methods, with their simplified approach in accounting for the dynamic effects, should be questioned. In an energy labelling context this simplified approach might prove sufficient and worthwhile. Yet, when aiming for a correct representation of residential energy use, which is, amongst others, determined by highly dynamic user behaviour, the static methods might have to be abandoned.

2.5 Overview and conclusions

This chapter started with defining the shortfall as the difference between calculated and measured energy savings, expressed as a percentage of the calculated savings. Although most attention is typically paid to the calculated savings, it was shown how also the measured energy savings must be well-understood. One has to be aware there is no such thing as the 'one and only true measured energy saving'. The outcome can be blurred by different approaches (longitudinal vs. cross-sectional), by the use of the rather simple heating degree days weather normalization, by the arbitrary splitting of space heating from total energy use, . . .

The empirical evidence showed a wide variety in shortfall values, ranging from 26 to 68 %, with 50 % being a reasonable estimate of typical shortfall in residential retrofitting programs. With shortfall easily being as large as 50 %, it is important to get insight in the possible causes. These have been ordered in 3 main categories.

Firstly, the rebound effect is discussed, in which the inhabitants take back part of the energy saving by an increased comfort level. This economically driven, purely behavioural, phenomenon is strongly linked with the temperature takeback, being the observation of an indoor temperature rise after retrofit. Dynamic building energy simulations have revealed how this temperature takeback, apart from a behavioural aspect, also has a physical aspect. If a realistic behavioural model is used including both intermittent and zonal heating, like will be done in this dissertation, this physical aspect will be automatically accounted for in the energy saving prediction.

Secondly, the (unexpected) technical issues are handled. Typical examples are the disappointing in-situ performances of retrofit measures (like uncomplete cavity wall filling or boilers not achieving their expected efficiencies) or the inevitable occurrence of thermal bridges following a building envelope insulation. Yet, a small case study concerning the latter indicated that the impact on the energy savings could be rather limited, certainly when good detailing levels are adopted. Also, the post-retrofit boiler efficiency drop has been discussed. In contrast, replacing windows or insulating pitched roofs have proven to lead to an unexpected airtightness improvement, beneficially reducing the heat losses due to air in- and exfiltration.

Thirdly, and possibly most importantly, the energy performance gap is mentioned as possible reason for shortfall. The empirical evidence has shown how quasi-steady state energy labelling tools, widely used as an easily accessible predictive tool, systematically overestimate the pre-retrofit energy use by 50 %. Hence, as retrofits cannot save energy that is not actually being consumed, shortfall is inevitable. Some major modelling issues are pointed out, of which the incorrect assumption of standard, high-comfort dwelling use is believed to be the most important one. A great deal of this research work is therefore dedicated to developing a more realistic user behaviour implementation. Furthermore, the simplified modelling of air change rates and the inability of quasi-steady state methods to correctly incorporate the dynamic effects, are named.

Overall, this chapter has focused on the occurrence of shortfall and on how it can be explained at the individual dwelling level. In the two following chapters, an improved building-physics based predictive method is developed, tackling many, yet not all, of the previously described phenomena and shortcomings. By lack of data for example, the (economic) rebound effect cannot be implemented within the improved methodology. Nevertheless, the overall methodology is still believed to be worthwhile in assessing more realistic energy savings.

3

Development of probabilistic behavioural model

The previous analysis of the shortfall illustrated how an incorrect implementation of user behaviour can lead to large deviations between real and calculated energy use for space heating. Therefore, the development of an evidence-based probabilistic user behaviour model, applicable to residential buildings, is handled in detail in this chapter.

3.1 Methodology

User behaviour can be seen as the overall term for a widespread range of user actions affecting the total energy use for space heating of a dwelling. It is typically divided in the following domains:

- **occupancy level**: presence of occupants, number of occupants
- **activity**: absent, sleeping, cooking, working, . . .
- **heating preferences**: thermostat settings, heating periods, (night) setback, heating behaviour in less inhabited zones (e.g. sleeping rooms)
- **cooling preferences**: use of passive cooling like lowering shading devices or night ventilation by opening windows, switching on cooling devices
- **ventilation preferences**: window and door opening, control of the ventilation system, opening/closing of ventilation grilles
- **use of appliances**: number of appliances (e.g. lighting and cooking devices, dishwasher, tumble dryer, . . .), type, frequency of use

The overview in this chapter will make clear how each of these user actions can take up many different values, with some values being more plausible than others. Yet, even if each of these user actions could be quite straightforwardly described separately, the reality proves to be much more complicated. Many of the above user actions do not occur independently, but are simultaneously influenced by many factors, called '*drivers*'. These are typically classified as follows:

- **household characteristics**: income, age, household size, employment status
- **building characteristics**: size, type, age, insulation level, type of heating/ventilation system
- **outdoor climate**: external temperature, solar radiation, wind

A schematic overview of how the user behaviour and the residential energy use for space heating are affected by the ensemble of these drivers is given in Figure 3.1. For example, households with a high level of income are likely to live in larger dwellings (Guerra Santin et al. 2009), thereby increasing the energy use for space heating. However, they are also more likely to be fulltime employed (ECS database, see further section 3.4.2) and thus require no heating during the day, thereby decreasing the energy use for space heating. When aiming for a representative and reliable estimation of the energy use at building stock level, an attempt should be made to translate this highly entangled and complex reality into a representative yet manageable behavioural model.

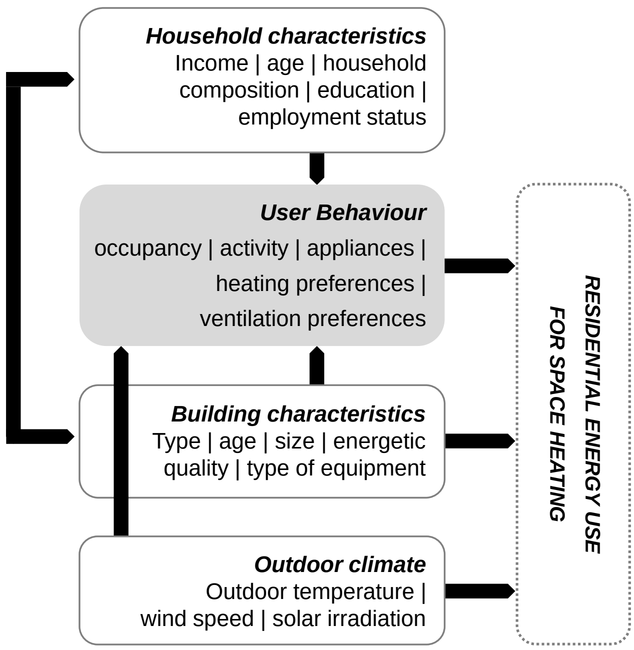


Figure 3.1: Schematic overview of the drivers for user behaviour and the link with residential energy use for space heating.

Set-up of the probabilistic behavioural model

When trying to capture the complex reality, it should be clear that the conventional approach in building energy simulations must be abandoned. In this approach, the user behaviour is conceived in a simplified manner by implementing a single user, often assumed to represent the 'average' user. However, by relying on only one deterministic user profile, the real-life complexity of user behaviour cannot be captured and no insight can be given on the uncertainty of the final outcome: what if other users are to inhabit the dwelling? what is the global uncertainty on the predicted energy use, and thus, energy savings, due to the inherent uncertainty about who is to inhabit the dwelling? Also, defining an 'average' user is not as straightforward as it might seem. Taking the average values for each of the above user actions does not necessarily lead to an average user profile, because it is possible that in reality the individual actions are unlikely to occur simultaneously.

Therefore, it is decided to follow a different path. A behavioural model is set up that is both (i) probabilistic and (ii) able to include the influence of drivers on the user behaviour. The first feature is fulfilled by expressing the input parameters as probability distributions instead of deterministic values. The well-known Monte-Carlo method can then be used to assess the output as a probability distribution, reflecting the global uncertainty about who is to inhabit the dwelling. The second feature is fulfilled by mutually linking the input parameters with correlation coefficients. When collecting these coefficients in a correlation matrix, this matrix can be used in the Monte-Carlo framework to convert the otherwise uncorrelated input parameters to correlated input parameters.

Outline of the chapter

The mathematical concepts behind the probabilistic set-up of the model are first briefly described (3.2). As reliable probability distributions for each of the input parameters strongly contribute to the overall reliability of the behavioural model, much effort is put in collecting evidence-based distributions (3.3). Afterwards, both a literature review and an analysis of the Belgian Energy Consumption Survey (ECS) are performed to gain insight in the relevance of the aforementioned drivers and the feasibility of implementing them into the behavioural model (3.4). Eventually, the final probabilistic behavioural model is presented (3.5).

3.2 Statistical and mathematical concepts

3.2.1 Spearman's rank correlation coefficient

Whenever it is important in this work to know how strongly two variables are related to each other, the *Spearman's rank correlation coefficient* $\rho_{i,j}$ is used. This coefficient measures the strength of association between two ranked variables. It assesses how well the relationship between variable i and j can be described by using a monotonic increasing or decreasing function. $\rho_{i,j}$ varies between -1 (perfectly monotonely decreasing relation) to 0 (no monotonic tendency) to +1 (perfectly monotonely increasing relation).

The Spearman's rank coefficient is chosen here as it is a non-parametric measure (there is no requirement of normality in the data) and as it uses ranks to calculate the correlation. The latter implies that both numerical variables and ordinal variables[1] can be used. Also, no assumption has to be made on the type of monotonic relationship. This is in contrast with the other most commonly used *Pearson product-moment correlation coefficient* which only measures the strength of the 'linear' relationship between the (numerical) variables.

For every correlation coefficient, permutation tests are performed to test if the null hypothesis $-H_0 : \rho_{i,j} = 0$, or in words, there is no association between the two variables− can be rejected. In general, a rather strict critical significance level of $\alpha = 0.001$ is adopted here. If the p-value of the test statistic is lower than this critical α-level, the test statistic is highly unlikely to occur under the null hypothesis and the null hypothesis can be rejected. Or, if the p-value is sufficiently low, the correlation can be assumed to be significantly different from zero. Remark how this p-value gives no information about the strength of the relationship: statistically significant, yet very low (<0.1) correlation coefficients are still possible.

3.2.2 Probabilistic modelling: Monte-Carlo method

For the probabilistic modelling in this work, the well-known Monte-Carlo method is used. It refers to the 'repeated execution of a deterministic simulation model $f(x)$ for different values of the input parameters X in order to estimate the probability distribution of the output parameters Y', like done in e.g. Van Gelder (2014)) and illustrated in Figure 3.2. Applied on the context of this work, the input parameters X are the different user actions like heating set-point, internal heat gains, occupancy levels etc. while the output Y will be the energy use for space heating, generated by means of a deterministic building energy simulation model.

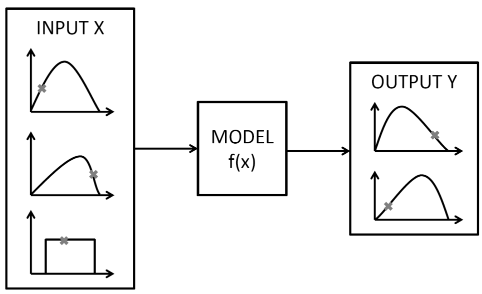


Figure 3.2: Schematic overview of the Monte-Carlo method. Source: Van Gelder (2014)

Common sampling techniques

Different techniques exist to sample from the input parameter distributions. *Simple Random Sampling* is widely used and very straightforward. Following Macdonald (2009) 100 simulation runs in

[1] An ordinal variable is a categorical variable (=having two or more categories) of which the categories can be put in a clear, meaningful ordening. For example, the age category of the head of a family is an ordinal variable as it takes values from 1 to 5, representing 5 different age categories ranging from young to old. For the use of the Spearman rank's coefficient, these categories do not need to be equally spaced.

a simple random sampling scheme should be sufficient in typical building simulation applications. A more efficient sampling technique is the *Latin Hypercube Sampling* (LHS). It divides the range of each variable into n equally probable intervals in which one sampling point is randomly chosen. As such, less sampling points and thus less simulation runs are needed. To allow for an even more efficient coverage of the sampling space, a space-filling LHS design can be constructed. Here, a uniformity-based sampling design is chosen, minimising the discrepancy of the set of sampling points[2] –for more details, see Janssen (2013). The resulting sampling scheme for p input parameters X and n simulation runs is then reflected in the $n \times p$ matrix R. In contrast with the findings of Macdonald (2009) it is found in this dissertation that, even when using the more efficient space-filling LHS sampling scheme, at least $n = 200$ simulation runs are needed to obtain a reliable output distribution (see further in Chapter 4).

Correlated sampling technique

The previous sampling schemes all generate input values that are uncorrelated. Yet, when some input parameters are correlated (e.g. the age of a dwelling can be correlated to its insulation level), a different approach must be followed. To do so, the $p \times p$ correlation matrix C must be built, containing all correlation coefficients of the input parameters X. C is then to be decomposed into matrix U:

$$C = U^T U \tag{3.1}$$

The two most common methods to do so are either a Cholesky decomposition or an Eigenvector decomposition (also known as a spectral decomposition or principal component analysis). Following the recommendations of Van Gelder (2014), the Eigenvector decomposition is used, as it is preferred when applying a space-filling LHS scheme. Having obtained this matrix U, one can generate correlated random numbers R_c from the uncorrelated numbers R:

$$R_c = RU \tag{3.2}$$

The ability of generating these correlated numbers by relying on the correlation matrix C will prove to be a major feature of the behavioural model. Not so much because it mutually links parameters to each other, but more importantly, because the way the linking is done is able to maintain the probabilistic nature of the parameters involved. In Figure 3.3 the above procedure is illustrated by showing the LHS sampling points of two normally distributed parameters that range from being uncorrelated (ρ=0) to completely correlated (ρ=1). When ρ=1, the use of a correlation coefficient is redundant: sampling one parameter unequivocally determines the values of the other parameter. However, as soon as correlations are less strict (e.g. 0.3 or 0.8), the procedure incorporates the tendency between the two variables, thereby respecting both probability distributions. Or, both parameters are

[2]The `MATLAB`-code to generate a uniformity-based latin-hypercube sampling design is provided by the author of Janssen (2013).

able to maintain their own probabilistic nature but can still be linked to each other to a greater or lesser extent.

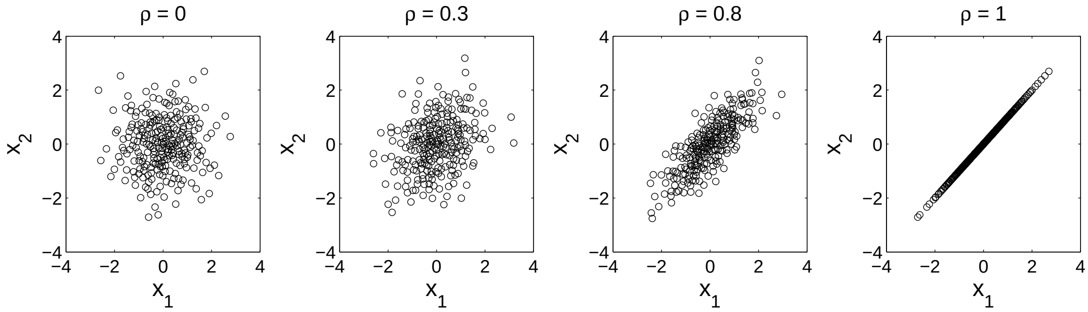


Figure 3.3: Latin-Hypercube sampling points of two normally distributed parameters when different correlations are adopted.

3.3 Individual user behaviour aspects

In this section, every user behaviour action is discussed separately. An in-depth literature review is always the starting point, revealing which data is already available and which data is lacking. Priority is given to these data sources that allow for a probabilistic assessment of the user behaviour action. The review is followed by how the specific user behaviour action is implemented into the behavioural model. Where data is missing, pragmatic assumptions are made. Overall, one should keep in mind that the final behavioural model is meant to be used in a large-scale building stock framework. This means that priority is not always given to detailed high-resolution models, yet that, whenever possible and feasible, a pragmatic approach is followed by using simplified models.

Occupancy patterns form an important preprocessing step in the behavioural model and are discussed first (3.3.1). Primary attention is then given to the heating preferences. Since these preferences cover a wide range of behavioural decisions/actions, they are subdivided in set-point temperature (3.3.3), (night) setback (3.3.4), heating schedules (3.3.5) and the heating behaviour in less inhabited parts of the dwelling (3.3.6). The ventilation preferences (3.3.7) and the use of appliances (3.3.8) are discussed afterwards. As the energy use for space cooling and hot tapwater is not considered in this work, no information on cooling preferences or hot tapwater use will be given.

3.3.1 Occupancy and activity levels

In terms of building energy simulation, the assessment of reliable occupancy periods and related activity levels is important both for the allocation of heating schedules and the production of internal heat gains. When someone is home and awake, it is quite likely that the heating system is switched on and high internal heat gains occur. As such, the assessment of occupancy and activity levels is a necessary and important preprocessing step in the behavioural model.

Literature review

Occupancy and activity levels are treated here together, as most existing models provide a solution for occupancy as well as for activities (Aerts et al. 2014). Well-known residential occupancy models are the models from Richardson et al. (2008), Widén and Wäckelgård (2010), Wilke et al. (2013) and the more recent model from Aerts et al. (2014). The modelling process in these studies is typically based upon surveyed time-use data, describing what people do and when, often classified into three occupancy states: at home and awake, sleeping and absent. An average occupancy profile, as illustrated in Figure 3.4, can then easily be deduced, giving the probability a household member is in a specific state throughout the day.

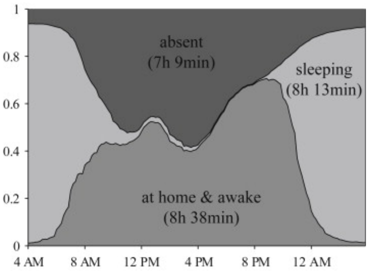


Figure 3.4: The average occupancy profile (based here on Belgian time-use survey data) indicates the overall probability that individuals are at home and awake, sleeping or absent. Source: Aerts et al. (2014)

Subsequently, Markov Chain processes are used to generate transition probability matrices, defining the probability at each discrete time step that a user switches to a different state, given the previous state and time of day. This leads to the generation of daily individual, stochastic occupancy sequences with a time-resolution of typically 10 minutes. One of the main disadvantages of this approach is that the duration of an activity is often not consistently modelled (Wilke 2013). A more refined model is therefore developed by Wilke (2013) in order to also include the probability distribution for the duration of the occupancy state, leading to more realistic activity/occupancy durations.

However, this overall procedure of generating probabilistic occupancy patterns does not allow for the consistent modelling of a specific household type throughout the year. Every time step again, probabilities are assigned with a limited memory considering the previous time step, still with no correlation whatsoever with the occupancy pattern of the previous day(s). This is in contrast with real-life occupancy patterns, where a great variety amongst different households is indeed found, but yet a limited variety within the same household (Weihl and Gladhart 1990). In addition, the current research work aims at energy use for space heating on the long-term (heating season), making the daily and stochastically defined small time-step variations in occupancy less important than the overall knowledge about the yearly average behaviour . One would thus benefit from a representative range of deterministic household profiles, each with their own chance of occurrence within the total population and each reflecting the typical average occupancy pattern of that type of households. This kind of information has recently been found in the work of Aerts et al. (2013, 2014) and is further discussed hereunder.

Implemented model

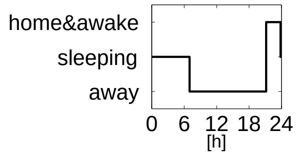
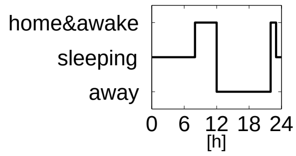
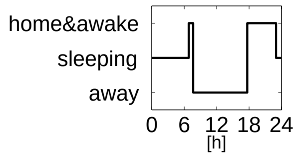
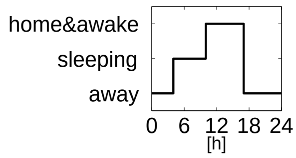
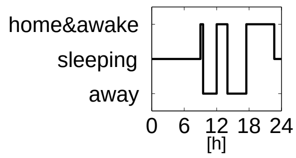
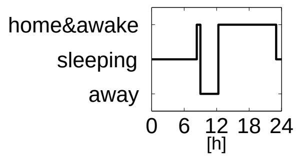
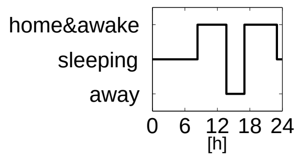
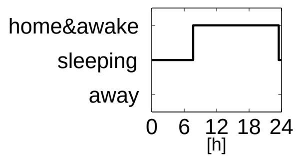
In this work, the occupant presence will be based on the work done by Aerts et al. (2013, 2014). They performed a cluster analysis on a Belgian Time-Use Survey, containing detailed information on the whereabouts and activities of 6400 respondents from 3474 households with a time resolution of 10 minutes. Using hierarchical clustering, they determined different subgroups within the population showing similar behaviour, leading to 7 probabilistic occupancy profiles that apply to week- and weekenddays. On request, the main author (Dorien Aerts) derived for us the 7 deterministic profiles, based on the clustering in Aerts et al. (2014).

The Time-Use Survey was combined with a Household Budget Survey (Aerts et al. 2013), thereby forming a rich dataset that contains not only the respondent's profile number for the week and weekendday but also its income, age and employment status. This is interesting, because one expects the occupancy profiles to be linked with the household characteristics. For example, the older the respondent, the more likely that he/she is at home during the day. Similarly, the higher the income, the more likely that the respondent is working fulltime. Also, the kind of week profile could be correlated with the kind of weekend profile. Incorporating these sorts of correlations into the behavioural model could seriously enhance its overall consistency and reliability. On request, these data was also provided by Dorien Aerts.

For the analysis in this research work, only the head of the households (HoH) are considered, reducing the original dataset from 6400 respondents to 3297 HoHs. As such, a dataset is obtained of 3297 respondents with their respective week- and weekend profile, age, income and employment status. This is necessary to obtain a population sample that is comparable with the Belgian ECS-database population (see later in section 3.4.2), where only HoHs are considered. For that same reason, the provided variables age, income and employment status are recoded so that they are in accordance with the categories of AGECAT, INCOME and ACTIVITY from the Belgian ECS-database (see Table 3.15).

In Table 3.1 the 7 profiles deterministic profiles from Aerts et al. (2014) are shown, now ranked in order of increasing hours at home (leading to different profile numbers than found in Aerts et al. (2014)) and with the empirical frequencies based only on the head of the households (leading to different frequencies than found in Aerts et al. (2014)). These profiles will be used to set the heating time schedules within the dwellings. It is important to note that the cluster analysis in (Aerts et al. 2013, 2014) has been performed on the respondent level and not on the household level. The deduced profiles thus do not state how many people are currently present, they only depict if the respondent is in the dwelling and if so, what he is doing. Due to privacy contraints it is not known which respondents (of the original enlarged set) belong to which household, impeding the construction of household occupancy profiles. This forms a minor drawback for use in the behavioural model, as a household occupancy profile is the resultant of different respondent profiles, probably leading to higher number of hours of presence in the dwelling. Nevertheless, these repondent profiles can still serve as a good approximation for household occupancy −one should just keep in mind

Table 3.1: Overview of the 7 deterministic occupancy and activity profiles and their empirical frequency, derived from Aerts et al. (2014) and ranked in order of increasing hours 'home and awake'[b].

Nr.	*Profile*	*Empirical frequency WEEK*	*Empirical frequency WEEKEND*
1		18 %	11 %
2		7 %	9 %
3		30 %	10 %
4		2 %	6 %
5		7 %	15 %
6[a]	 	24 %	34 %
7		13 %	15 %

[a] In the work of Aerts et al. (2014) this pattern is denoted as 'short daytime absence'. It is characterised by a short absence during the day, either in the morning or afternoon. Two deterministic profiles are derived for this pattern, each with equal probability of occurrence.

[b] The profile numbers given here are different from the profile numbers used in Aerts et al. (2014).

that the total hours of household presence might be somewhat higher than reflected by the profiles from Table 3.1. Moreover, no other options are available, both applicable within the Belgian context and offering the same amount of representativeness, detail and feasibility for implementation in a stochastic framework.

In addition, a correlation analysis is performed here to discover tendencies between the kind of occupancy profile and the socio-economic characteristics. The correlations analysis is performed by calculating Spearman's rank correlation coefficients, given in Table 3.2.

Table 3.2: Spearman's rank correlation coefficients (all significantly different from zero at the α = 0.001 level) between socio-economic variables and the profile numbers for week and weekendday from Table 3.1.

	AGECAT	INCOME	ACTIVITY	PROFILE_{WEEK}	$\text{PROFILE}_{WEEKEND}$
AGECAT[a]	1	-0.15	-0.71	0.42	0.20
INCOME[b]		1	0.44	-0.26	-0.09
ACTIVITY[c]			1	-0.54	-0.20
PROFILE_{WEEK}				1	0.25
$\text{PROFILE}_{WEEKEND}$					1

[a]Ordered from young to old
[b]Ordered from low to high income
[c]Ordered from retired (1) and at home (2) to working part-time (3) and full-time(4)

The week profile is clearly correlated the strongest to the socio-economic variables. The higher the age of the head of the household (+0.42) and the lower its income (-0.26) and activity level (-0.54), the more likely that he/she falls under the high profile numbers (most hours home and awake). Figure 3.5 visualises these correlations via density scatterplots. For the weekend profile, similar tendencies are found though much weaker. Also, it is revealed how both week and weekend profile are moderately correlated (+0.25) to each other. Both the strong statistical significance, the relatively high correlation coefficients and the fact that they fulfill the expected tendencies, give good confidence that the values obtained in Table 3.2 are meaningful and useable in the behavioural model.

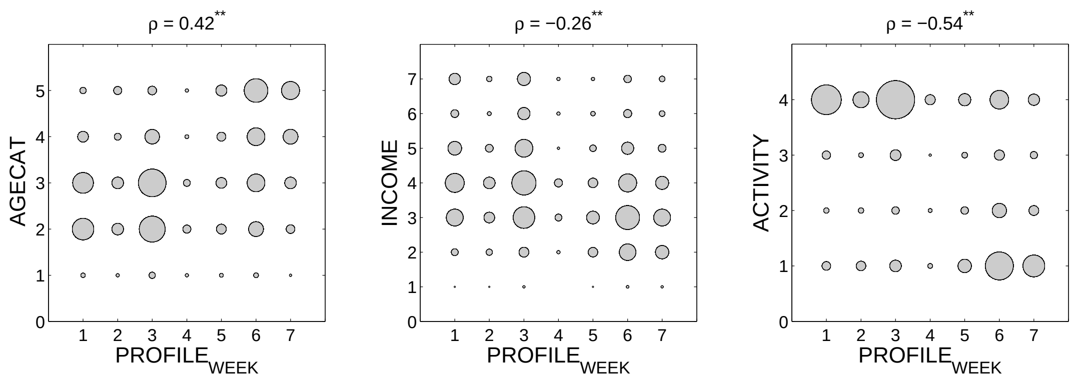


Figure 3.5: Density scatterplots between the week profile number and the household characteristics AGECAT, INCOME and ACTIVITY (the sizes of the circles are proportional to the frequency of occurrence).

Overall in this behavioural model, the sampling of a household occupancy pattern for a week- and weekendday (based on the empiricial frequencies of Table 3.1) will serve as the preprocessing step, correlated through the correlation coefficients of Table 3.2 to the household characteristics sampled from the ECS-database. Based on this sampled profile, many other parameters of the behavioural model can be set, like the heating preferences (e.g. lower temperature settings are expected during sleeping hours and hours of absence) or time-dependent internal gains (e.g. low levels during sleeping hours and absence, higher levels during hours of awake presence). The exact coupling between the occupancy profile and each of these parameters will be further explained throughout this chapter.

3.3.2 Heating preferences: general

Before moving into the heating preferences, two general comments must be made regarding (i) the predominant heating system in Belgium and (ii) thermal comfort in residential buildings.

Predominant heating system in Belgium

Although the heating system will not be explicitly modelled in the building energy simulations of this research work (see Chapter 4), it is important to clarify which kind of heating system and temperature control is kept in mind when setting up the behavioural model, because the kind of system can influence the occupant's behaviour. Delghust (2014) for instance observed much lower bedroom heating probabilities in old than in newly built dwellings, which could partially be explained by the old dwellings only having local (and expensive) electrical heaters in the bedroom, in contrast with newly built dwellings having a central heating system throughout the dwelling. Also the type of temperature control (manual vs. programmable thermostat, regular versus thermostatic valves, . . .) can play a role in how occupants behave (Nevius and Pigg 2000, Jeeninga et al. 2001, Tachibana 2010).

The following heating system is predominant in Belgium and therefore used as basis for the behavioural model: a hydronic central heating system with radiators and/or convectors with thermostatic valves and regulated by a programmable on/off room thermostat in the main living room[3,4,5]. Within this system, all radiators (and thus rooms) will follow the time schedule as implemented within the central room thermostat. As a consequence of this system, all rooms other than the main living room are dependent to what happens in that main living room. If the room thermostat is off, no heat is supplied to the system −even if for instance the desired set temperature in the bathroom is not yet

[3] In the ECS-database (VITO et al. 2012a) 85 % of all 3396 households have a central heating system in their dwellings (either individual or collective), and 96 % of these systems is equipped with radiators and/or convectors - see further Figure 3.18 on page 81.

[4] Following a survey on 56 Belgian households with central heating in Peeters et al. (2008), 95 % of them are equipped with radiators/convectors. 80 % of the 56 households controlled the heat emission by a central room thermostat with thermostatic valves (TRVs), 18 % had a central thermostat without TRV and 2 % had no central thermostat and only TRVs.

[5] Following the energy survey of 1004 Flemish households by TNS (2013), 51 % has a programmable on/off room thermostat, 28 % has a manual on/off room thermostat, 10 % has a weather-dependent thermostat and the remaining 10 % is not able to regulate the temperature at all.

reached. If the room thermostat is on, local temperature control is possible in the rooms other than the main living room[6] by turning down/up the thermostatic radiator valves.

Thermal comfort in residential buildings

Many conventional standards adress six primary factors for the determination of thermal comfort (ASHRAE 2004, ISO 7730 2005): air temperature, radiant temperature, air velocity, humidity, metabolic rate and clothing insulation. Under normal conditions, mostly typical to office spaces (sedentary activity, normal clothing, limited air speeds, humidity within certain bandwidths - for exact values see ISO 7730 (2005)), the operative temperature T_{op} can be taken as single indicator of indoor comfort, with an allowable range of [21 - 23] °C. It is defined as

$$T_{op,i} = 0.5T_{air,i} + 0.5T_{rad,i} \qquad [^{\circ}C] \tag{3.3}$$

with $T_{air,i}$ and $T_{rad,i}$ the indoor air and mean radiant temperature respectively. When designing new buildings, the allowable operative temperature range can serve as one of the design criteria. However, when simulating actual energy use of existing buildings, this comfort range cannot be used because it does not necessarily correspond to actual indoor conditions. For example, the large-scale thermal comfort study of Hong et al. (2009) showed actual indoor comfort of UK low-income households to be far below the above comfort range.

Also, difficulties arise when one needs to characterise the 'actual indoor condition'. For example, there is no such thing as an 'indoor room temperature'. Instead, there are dry air bulb temperatures, (mean) radiant temperatures, surface temperatures, operative temperatures, ... Care is thus taken in this section to accurately indicate which temperature is actually meant for. Furthermore, the translation of 'actual indoor condition' into a specific parameter of a simulation model is often not straightforward. Typically in a building energy simulation environment, the control of the heating system is based on reaching the required operative temperature. This is not done in this work because (i) one cannot rely on the previously given design ranges of operative temperature to represent actual indoor condition and (ii) large-scale information on actual operative temperatures in existing residential buildings is very scarce. Instead, and as also further elaborated in 4.5.1, the heating system of the building energy simulation model is regulated on the following temperature reference indoor temperature $T_{ref,i}$:

$$T_{ref,i} = 0.75T_{air,i} + 0.25T_{rad,i} \qquad [^{\circ}C] \tag{3.4}$$

As explained further on, this temperature $T_{ref,i}$ quite well reflects the temperature as measured by a room thermostat or a conventional temperature logger (e.g. HOBO-logger). This makes it a temperature accessible both from surveys and questionnaires (when asking the inhabitant about its indoor temperature, it is most likely he refers to the temperature displayed by his room thermostat)

[6] In order not to interfere with the central room thermostat in the main living room, the radiator valves of the main living room should (and are assumed to) be regular (and not thermostatic) valves in always fully opened position.

and from indoor temperature measurements campaigns, enabling its availability on a larger scale than the operative temperature.

3.3.3 Heating preferences: set-point temperature

Literature review

Estimates of the set-point temperature both based on self-reported (interviews and questionnaires of the households) and on measured data will be briefly discussed.

Self-reported set-point temperatures The estimates of the set-point temperature based on self-reported thermostat settings are summarised in Table 3.3 −information is also given on how each of the surveys asks about the set-point temperature, showing how care must be taken when comparing the results of different surveys in which (slightly) different definitions of 'set-point temperature' might be used.

The temperatures in the UK are remarkably lower than in the Netherlands or Belgium, suggesting lower heating levels and possibly also lower indoor thermal comfort conditions in the former. Interestingly, Shipworth (2011) repeated a survey from 1984 on a statistically comparable sample in 2007 to test the claim that households' comfort requirements have increased over time. Yet, no statisically significant difference was found between the thermostat settings of the 1984 and 2007-sample. Nor did building age, levels of roof insulation, double-glazing and draught-proofing had any statistically significant effect on thermostat settings. This suggests that the set-point temperature in the main living room is a rather invariant and insensitive thermostat setting.

When relying on reported heating behaviour, as in interviews or questionnaires, one should be aware that there can be some discrepancy between what people report and what is actually programmed. In addition, in most cases, people will report the temperature they program on their central room thermostat. Apart from calibration errors of the room thermostat itself, other errors are

Table 3.3: Overview of self-reported set-point temperatures.

Authors	*Country*	μ [°C]	σ [°C]	*n*	*Question asked in survey*
Shipworth et al. (2010)	UK	19.00	3.00	164	'Thermostat setting?'
Shipworth (2011)	UK	19.30	2.70	111	'Thermostat setting?'
Guerra Santin et al. (2009) (*KWR database*)	NL	20.28	1.62	15 000	'Temperature during the evening?'[a]
Guerra Santin and Itard (2010) (*WoON database*)	NL	20.08	2.15	242	'Temperature during the evening?'[a]
ECS-database (see Section 3.4.2)	BE	20.74	1.66	3165	'Temperature in main living room when someone is home and awake?'

[a] In both NL-surveys, the respondents were questioned about the temperatures during the day, the evening and the night. The 'temperature during evening' is taken here, as it is believed to best approach the set-point temperature. The temperatures 'during day/evening' are shown further below in *Table 3.5 Overview of reported setback temperatures.*.

induced as it remains unknown which temperature is actually measured by the thermostat. Room thermostat systems measure mainly the dry air bulb temperature, but the sensor is also influenced by the temperature of the wall at which the thermostat is fixed and the radiant temperature of the surrounding room (Olesen 2001). The radiant temperature can not be neglected, but its influence is hard to determine; local air flows and nearby radiant sources alter the measured temperature to a great extent (Van der Veken et al. 2006). Nevertheless, based on Van der Veken et al. (2006), it is appropriate to consider the temperature, measured by a room thermostat, as a mixture of 75 % air temperature and 25 % radiant temperature.

Set-points derived from measured indoor temperatures Apart from self-reported thermostat temperatures, one can also rely on measured indoor temperatures, as is done by two studies (Shipworth et al. 2010, Huebner et al. 2013a). Both studies use the same large dataset from the UK CaRB-project (Carbon Reduction in Buildings) that contained 45-min interval spot indoor temperatures measurements in 358 households. The results are given in Table 3.4.

Table 3.4: Overview of set-point temperatures, deduced from air temperature measurements in the main living room.

Authors	*Country*	μ [°C]	σ [°C]	*n*
Shipworth et al. (2010)	UK	21.10	2.50	195
Huebner et al. (2013a)	UK	20.47	2.47	248

The analysis of Shipworth et al. (2010) relies on the assumption that "*living room temperatures only increase when the central heating system was in use*". This is a rather questionable assumption as the indoor temperature might also rise due to incident solar gains or internal gains, without the heating system being in use. To somewhat account for this, particularly in cases where occasional rises occurred in houses where the heating was clearly off all day, any day with less than 2 hours of total active heating duration was excluded. On days with more than 2 hours heating duration, the maximum living room temperature was taken to be the thermostat setting used on that day. This again ignores possible increases of the temperature due to other heat sources and thus easily leads to an overestimation of the actual setpoint temperature. As could be expected, the mean setpoint temperature (21.1 °C with σ = 2.5 °C), as estimated from the loggers, was about 2 °C higher than the reported setting (see Table 3.3 - Shipworth et al. (2010)).

Huebner et al. (2013a) used the same dataset but introduced some essential improvements to the analysis of Shipworth. Here, a sequence of increasing or decreasing temperatures was only considered to be a change in the state of the heating system, if the magnitude of the overall change was at least 0.75 °C. Differences due to any thermostat hysteresis or mini-fluctuations in the logger are thus ignored. Further on, in each sequence that was identified as having the heating on, the maximum temperature was identified as the set-point temperature for that sequence, as long as it was not the last data point and differed by 0.1 °C or more from the previous data point. For each dwelling, all estimated set-points for all sequences were averaged over all days, arriving at one value of the estimated heating set-point temperature per dwelling. This improved procedure lead to a lower mean estimated setpoint temperature of 20.47 °C (σ = 2.47 °C) across all dwellings.

In the measurement campaigns of Shipworth et al. (2010), Huebner et al. (2013a)) HOBO data loggers are used. Although they also mainly measure the air temperature, the influence of the surrounding radiant temperature cannot be neglected −similarly as with room thermostats. Hence, it is assumed they measure a similar temperature as the room thermostats, being 75 % air and 25 % radiant temperature.

Implemented model

From the previous literature review it can be concluded that all studies give quite similar estimations of the set-point temperature. This gives good confidence that the set-point temperature in the main living room can be reliably predicted. For this work, the results of the Belgian ECS-database are chosen. The setpoint temperature in the main living zone is thus estimated following the normal distribution *TSETPOINT ~ N(20.74 , 1.66)*, as shown below in Figure 3.6.

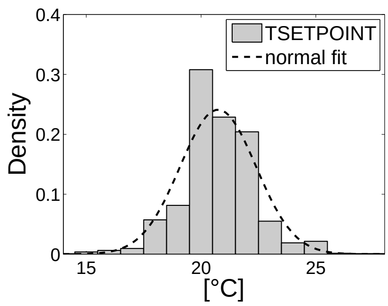


Figure 3.6: The empirical distribution of TSETPOINT of the Belgian ECS-database, best fitted with a normal distribution.

3.3.4 Heating preferences: (night) setback

Setback is defined here as the lowering of the setpoint temperature via the central thermostat in the main living room. It includes not only the fact whether setback is applied yes or no, but if so, also when and to which temperature.

Literature review

Only a few empirical studies considering (night) setback could be found. One example is a Swedish survey on energy behaviour in 600 households (Linden et al. 2006), in which 38 % of the households where the heating temperature could be lowered overnight, did not do so. This is somewhat higher than the value found in the recent Belgian ECS-database (see Figure 3.7), in which about 9+6=15 % of the households report to never apply night setback. Furthermore in this Belgian database, only 16 % apply the most economic regime -lowering the temperature both at night and for short absence periods during the day- while 9 % of the questioned households do not even apply any setback at all.

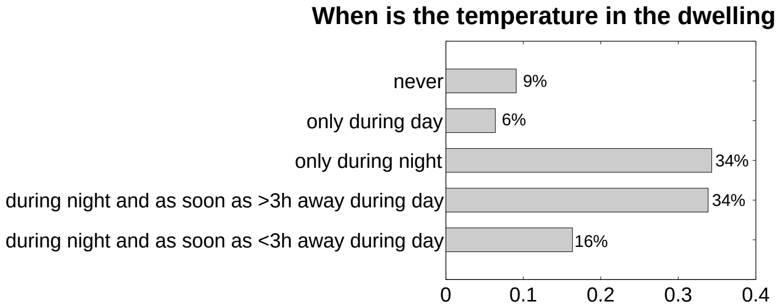


Figure 3.7: (Night) setback from the Belgian ECS-database (n=3389).

Apart from the fact whether (night) setback is applied yes or no, the question how setback is defined, is equally important. For some households, setback means lowering the temperature with only a few degrees while other define it as the heating system being totally switched off. Information on actual setback temperatures has only been found in two Dutch databases and in the Belgian ECS-database (see Section 3.4.2) −the information is summarized in Table 3.5 . It must be kept in mind though that the temperatures of the Dutch databases also include those cases where no setback is applied, possibly leading to (too) high estimates of actual setback temperatures, especially during day.

The empirical distribution of the ECS-database nighttime setback temperatures is given in Figure 3.8a, together with its fitted normal distribution (proved to give the best fit). By means of comparison Figure 3.8b shows the empirical distribution of the 'temperatures during night' of the Dutch KWR Database, as found in the work of Leidelmeijer and Grieken (2005). Both graphs show a very large spread in possible nighttime setback temperatures

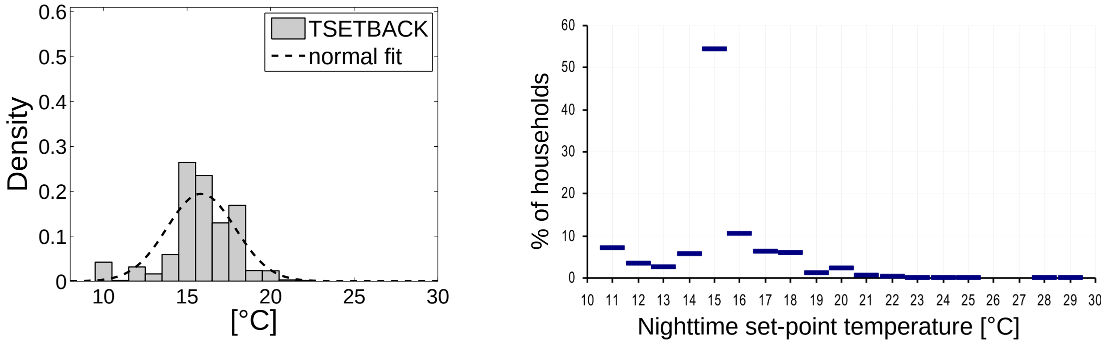
Table 3.5: Overview of reported setback temperatures.

Authors	*Country*	μ [°C]	σ [°C]	*n*	*Question asked in survey*
Guerra Santin et al. (2009) (*KWR Database*)	NL	19.29 14.76	2.23 2.27	15 000	'Temperature during day?' 'Temperature during night?'
Guerra Santin and Itard (2010) (*WoON Database*)	NL	18.89 15.81	2.63 2.58	~220	'Temperature during day?' 'Temperature during night?'
ECS-database (see Section 3.4.2)	BE	15.83	2.05	2834	'If setback is applied, what is temperature in main living room during night and when no one is at home?'

Implemented model

In the final behavioural model, setback in the main living rooms will be based on the results from the Belgian ECS-database:

- The empirical frequencies from Figure 3.7 are used to assess *when* setback is applied, reflected in the parameter WHENSETBACK.



(a) ECS-database - see Section 3.4.2

(b) Source: Leidelmeijer and Grieken (2005)[a]

[a] All households with a local gas heater, reporting to switch it off completely overnight, have been categorized under 15 °C.

Figure 3.8: Empirical distribution of reported nighttime set-point temperatures.

- The *amount of temperature setback* is not sampled from the setback temperature TSETBACK from Figure 3.8a itself, but is sampled from the difference between set-point and setback temperature: DELTAT = TSETPOINT - TSETBACK, shown in Figure 3.9. This is done, because (i) DELTAT proves to be better correlated with TSETPOINT than TSETBACK (see section 3.4.2), leading to a higher consistency in the behavioural model and (ii) because it ensures, with DELTAT being always positive, that TSETBACK is always smaller than TSETPOINT.

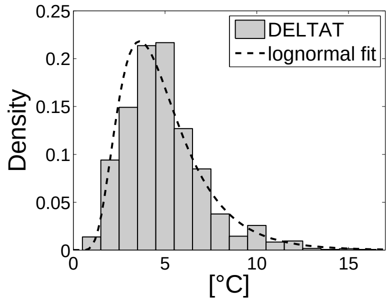


Figure 3.9: The empirical distribution of DELTAT of the Belgian ECS-database, best fitted with a lognormal distribution.
μ_{sample} = 4.9 °C; σ_{sample} = 2.17 °C; fit ~ LogN*(1.49 ; 0.46)*

3.3.5 Heating preferences: heating schedules

The two previous paragraphs revealed which temperatures are set in the main living room (TSETPOINT and TSETBACK) and when the temperature is typically lowered (WHENSETBACK). However, there is no coupling yet between this information and any real-life heating schedule during the day. This will be done in this paragraph.

To do so, the heating schedule is defined as the time periods during which the inhabitants want the heating system to meet their highest chosen temperature setting (typically the temperature set when someone is present and awake). The remaining part of the day, the heating system is thus either in a setback modus or completely switched off.

Literature review

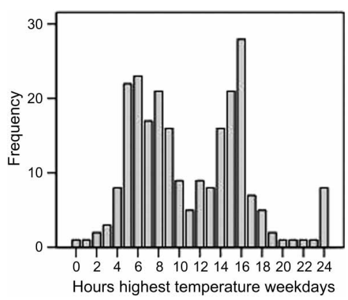
Ideally, information on the heating schedule should be obtained via direct monitoring and logging of the thermostat control system itself. Only by doing so, the information can be assumed objective and representative for the actual desired heating schedules of the households. However, no such monitoring studies could be found. Instead, studies are available that rely on (i) reported heating schedules via questionnaires and interviews, (ii) measured indoor air temperatures or (iii) measured radiator temperatures. An overview of the estimated heating duration times is summarized in Table 3.6.

Table 3.6: Overview of estimated daily mean heating durations (standard deviation in brackets), both for week- and weekenddays.

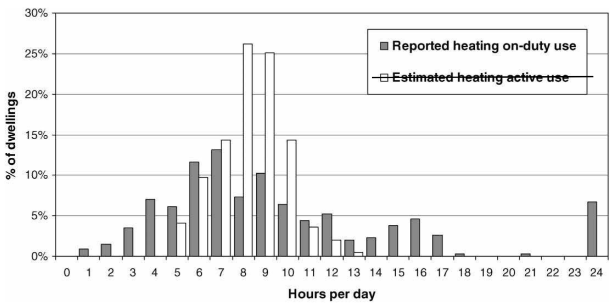
Authors		*Week* [h]	*Weekend* [h]	*n*	*Method*
Guerra Santin and Itard (2010)	NL	11 (5)[a]	-	236	Questionnaire
Shipworth et al. (2010)	UK	9.4 (5.4)	9.8 (5.4)	344	
Martin and Watson (2006)[a]	UK	8.78 (-)[b]	-	59	Temperature logger behind first radiator in the system
Shipworth et al. (2010)	UK	8.2 (1.5)	8.4 (1.5)	196	Air temperature measurements in main living room
Huebner et al. (2013a)	UK	9.8 (-)[b]	10.1 (-)[b]	248	

[a] Weekday and weekend data are weighted averaged into one estimate.
[b] No standard deviations were given.

Again an indication is found for the lower heating levels in the UK compared to the NL: the UK heating durations are lower than found in the (single) study in NL. When looking at the statistics as given in Table 3.6, one might conclude that the overall daily heating duration follows a normal distribution. However, when looking at the histograms as found in the questionnaire studies (Figure 3.10), it is clear how this is not the case.



(a) Source: Guerra Santin and Itard (2010)



(b) Source: Shipworth et al. (2010)

Figure 3.10: Histograms showing the reported daily duration the heating is on its highest chosen setting.

Both graphs clearly show a *trimodal* distribution, meaning that three different modes are present, visible by the distinct peaks. One mode occurs around [4-8] hours, representing the households who only heat in the morning and evening, while the second mode occurs around [15-16] hours, representing the households who keep on the heating system during the day and only lower/switch off the heating system at night. The third mode is reflected in the peak at the 24 h value, representing those households who never switch off the heating. Or, this histogram points out that how the heating time schedules are strongly linked to the times of presence of the inhabitants, an effect that cannot be fitted by a normal distribution. Remarkably, none of the authors have discussed the histogram in detail, nor did they point out the discrepancy between the disposed normal distribution values and the information found on the graphs. So, the statistics provided in Table 3.6 can only serve as a control parameter for checking the global reliability of implemented heating schedules, preferably based on occupancy profiles.

For the questionnaire studies in Table 3.6, the heating duration is the total time per day the household wants the comfort to be maintained in the dwelling. This is not to be confused with the actual operating time of the heating system, being the remaining values of Table 3.6. For example, if the indoor temperature rises above the upper threshold value of the thermostat, the heat production is temporarily switched off until indoor temperature falls again under the lower threshold value. This can happen several times within the same (desired) heating duration period. It is thus no surprise that the heating operation values are lower than the questionnaire values.

Martin and Watson (2006) estimate the operation time of the heating system by looking at the radiator temperature, monitored by a sensor mounted behind the first radiator on the system. The observed temperature differences are typically quite high, certainly in more traditional heating systems working with high water temperatures, so a relatively reliable algorithm could be developed deciding whether or not the heating system is changing state.

The second method to estimate the heating operation time relies on the indoor air temperature measurements of Shipworth et al. (2010) and Huebner et al. (2013a). As already mentioned, indoor temperature measurements do not allow to distinguish between temperature rises due to the heating system being on or rises due to other heat sources (internal / incident solar radiation), leading to a possible overestimation of heating operation time. The (improved) values of Huebner et al. (2013a) are indeed higher than the values of Martin and Watson (2006).

The information on heating time schedules is mainly found in the aggregated form of daily heating duration. However, in order to use realistic heating time schedules in dynamic building energy simulation tools, more detailed information is needed on the daily distribution of that total duration time across the day. One such example is found in the previously discussed work of Huebner et al. (2013a) where the average probability is deduced for the heating system being on - see Figure 3.11. However, the same objection applies for using these probability profiles for modelling household heating behaviour as it did for using probabilistic occupancy profiles (see Section 3.3.1). They do no allow to generate consistent household profiles across the year, as the generated actions only depend on the previous time steps, without any link to previous days. This is in contrast with real household heating behaviour: Guerra Santin and Itard (2010) found that 50.7 % of the questioned households almost always keep the thermostat on the same programme and 31.4 % only sometimes changed that programme. Therefore, these probability curves will not be used in this work.

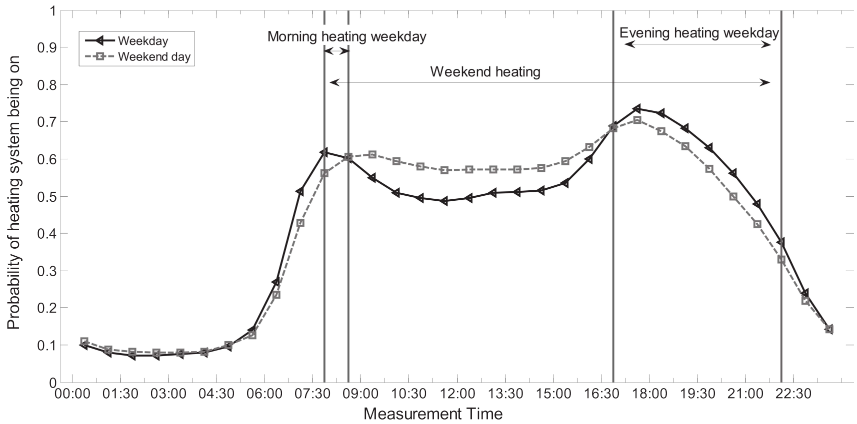


Figure 3.11: Average probability for the heating system being on for weekdays and weekends. Source: Huebner et al. (2013a)

Given the previous overview of heating schedules the main conclusions are:

- The trimodal distribution of the daily heating duration shows evidence of a strong link between occupant presence and heating times.
- Although different methods and definitions of total dailly heating duration are shown together in Table 3.6, there is a large similarity in the overall outcome: all mean heating durations are within the range of 8-10 hours in the UK context and 11 hours for one study in NL.
- Independently of the applied method, little variation is found between heating duration on week- and weekenddays. On weekenddays, the heating duration is indeed slightly higher, but the difference is small. This contrasts with common modelling assumptions, where a clear distinction is often made between week- and weekenddays.

Implemented model

As said, the averaged values of heating duration cannot be reliably used into the behavioural model. Instead, the trimodal distribution showed how it is a better option to link the heating schedules with occupant presence. To do so, the deterministic occupancy profiles from Section 3.3.1 are used. The combination of these profiles with the heating preferences parameters TSETPOINT, DELTAT and WHENSETBACK allow for a complete characterisation of the implementation of heating behaviour in the main living room.

The procedure is as follows. The sampling of the occupant profile is done in the preprocessing step. Then, when someone is home and awake, the demand temperature is always assumed to be the set-point temperature TSETPOINT. The demand temperatures in the 2 other states (away and sleeping) depend on the fact whether setback is applied yes or no, reflected in the parameter WHENSETBACK. Whenever setback is applied, the temperature imposed is always the same, being TSETPOINT − DELTAT. All this is summarized in Table 3.7. An example of the translation of all sampled parameters into a dayzone heating schedule is shown in Table 3.8.

Table 3.7: Overview of the different options in dayzone heating schedules, depending on the parameter WHENSETBACK and with the setback temperature defined as TSETPOINT − DELTAT.

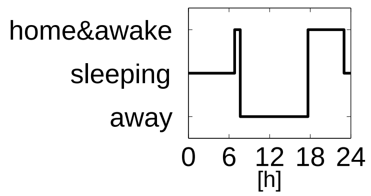
WHENSETBACK			Temperature assigned during each state home & awake	away	sleeping
1	never	9%	TSETPOINT	TSETPOINT	TSETPOINT
2	only during day	6%	TSETPOINT	setback	TSETPOINT
3	only during night	34%	TSETPOINT	TSETPOINT	setback
4[a]	during night and as soon as >3h away during day	34%	TSETPOINT	setback	setback
5[a]	during night and as soon as <3h away during day	16%	TSETPOINT	setback	setback

[a]For reasons of simplicity, options 4 and 5 are considered identical: as soon as the inhabitant is away, the setback temperature is imposed, regardless of the duration of the inhabitant's absence.

Table 3.8: Example to illustrate assessment of heating schedule in dayzone.

Sampled parameters

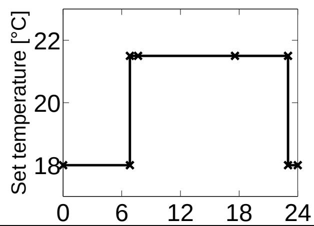
PROFILE$_{WEEK}$ =



WHENSETBACK	=	3
TSETPOINT	=	21.5 °C
DELTAT	=	3.5 °C

➡

Implemented heating schedule DAYZONE



3.3.6 Heating preferences: heating behaviour in less inhabited parts of the dwelling

All previous items concerned the heating behaviour in the main (living) room, in general the room where the thermostat of the central heating system is situated. Assuming that the rest of the dwelling is identically heated as the main living rooms would seriously overestimate the actual heat demand. Many studies can be found in the literature (Hunt and Gidman 1982, Janssens and Vandepitte 2006, Oreszczyn et al. 2006, Hong et al. 2009), all pointing out how only mainly the living rooms are heated to comfort temperature, while the remainder of the dwelling is heated at a considerably lower set-point temperature.

The heating in other rooms than the central thermostat room is in most cases regulated manually. Radiator valves are opened/left open/closed or local heaters are switched on/off depending on the wishes of the household. In order to be implementable into any dynamic building simulation program, data should be available that can at least answer this twofold question: when are the less inhabited rooms heated (e.g. when are radiator valves switched on/off) and to which temperature (e.g. to which position is the radiator valve turned (and is it a regular or a thermostatic valve?)? Unfortunately, little useful information can be found on this issue in the current literature.

Literature review

If information is found, it is mostly given qualitatively rather than quantitatively. The overall picture of all data sources gathered together could as such provide some insight in global tendencies. For example, different behavioural patterns have been deduced in the research from Leidelmeijer and Grieken (2005), based on the KWR database containing 15 000 Dutch households - see Table 3.9. Although 7 different behavioural patterns have been found, no substantial differences are observed between them - except from the energy-spending pattern 2, representing 17 % of the households, where all rooms (if present) are always heated. All other patterns show more or less equal behaviour: the living room and kitchen (if present) are almost always heated, the bedrooms are only rarely heated and the bathroom is regularly heated. All others rooms are either not present in the dwelling, not heatable or only rarely/never heated. This table is interesting since it provides useful information about whether or not a room is heated. However, it does not give any quantitative figures about the extent of the heating: does a 'heated bedroom' mean that the temperature is raised to the central living room temperature or does it mean that the (thermostatic) radiator valves are just continuously kept open at a certain position? This information is not found in the study.

Table 3.9: Summary of behavioural patterns in 15 000 Dutch households concerning the space heating in rooms: ++ = always heated, + = occasionally, - = rarely or never, o = no such room in dwelling or no heat source available. Source: Leidelmeijer and Grieken (2005)

	1	2	3	4	5	6	7
living room	++	++	++	++	+/++	++	++
kitchen	++	++/o	++/o	o	+/o	o	-
bedroom	-	++	-	-/+	+/-		-
bathroom	++/-	++	++		+	++	
scullery	o	o/++	++	o	o	o	o
attic	o/-	o/++	o/-	-/o	o	o	
enclosed porch	o	o/++	o	o	o	o	o/-
garage	o/-	o/++	-/o	o	o	o	o/-
share	23 %	17 %	11 %	15 %	6 %	19 %	9 %

In a recent survey on 1004 Flemish households (TNS 2013) the respondents were asked which rooms were heated during the day when someone was at home. It was explicitly mentioned that just keeping the rooms above freezing temperatures was not considered as 'being heated'. The results are shown in Figure 3.12. A similar trend is observed here: when people are at home, the living room and kitchen are almost always heated, bathrooms are regularly heated while the bedrooms are the least heated rooms.

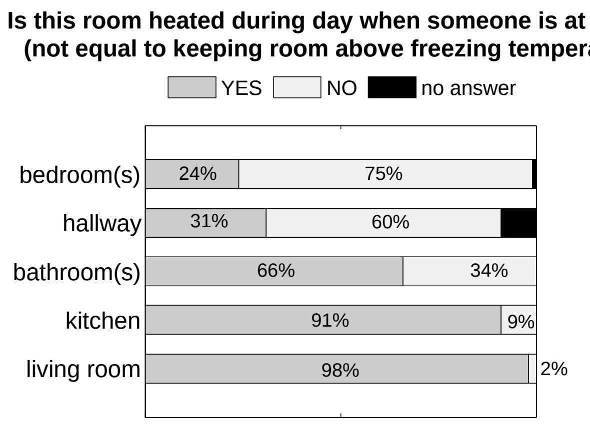


Figure 3.12: Heating behaviour in the different rooms of the dwelling, following an energy survey in 1004 Flemish households. Source: TNS (2013)

To gain further insight in the extent to which bedrooms are heated, it can be useful to look at measured indoor temperatures. Two studies are briefly discussed here.

The earliest evidence can be found in the frequently cited work of Hunt and Gidman (1982). They analysed indoor temperature measurements, performed in each room of 1000 houses in the UK during the whole month of March 1978. While the mean recorded living-room temperature was 18.3 °C (σ = 3) and the mean kitchen temperature 16.7 °C (σ = 3.1), the mean temperature of the warmest bedroom was only 15.2 °C (σ = 3.3). More interestingly, they found clear trends in the inter-room correlation of temperatures in the dwelling. Apart from the living room temperature, all other temperatures in the dwelling were strongly correlated, suggesting that temperatures in the rest of a home tended to follow each other closely: cold homes were generally cold throughout and warm ones were warm throughout. Also, the living room seemed to be maintained at a temperature which was more or less independent of those in the other rooms of the dwelling.

In the research of Janssens and Vandepitte (2006) 39 dwellings have been selected across Belgium, in which the indoor climate is monitored every 10 minutes in different rooms. The daily mean indoor temperatures have been sorted as a function of the daily mean outdoor temperatures, leading to the results of Figure 3.13. In these graphs the dependency of indoor from outdoor temperature reflects the extent in which heating is applied. As soon as the daily mean outdoor temperature increases above 15 °C, all rooms show more or less the same indoor temperatures, strongly dependent on outdoor temperatures, suggesting the heating systems are switched off and the dwelling is in 'free-flow-state'. Below this 15 °C outdoor temperature, it can be assumed that heating systems are switched on. As expected, the living rooms are quite continuously heated: the inside temperature is barely dependent of outside temperature. For bathrooms, a similar trend is found but with a larger spread: the median curve is rather flat but below it there exists a wide range of lower temperatures, suggesting these bathrooms are not or barely heated. The bedrooms show the strongest dependency with outdoor temperature, indicating that these types of room are only occasionally or even never heated in a large part of the investigated dwellings.

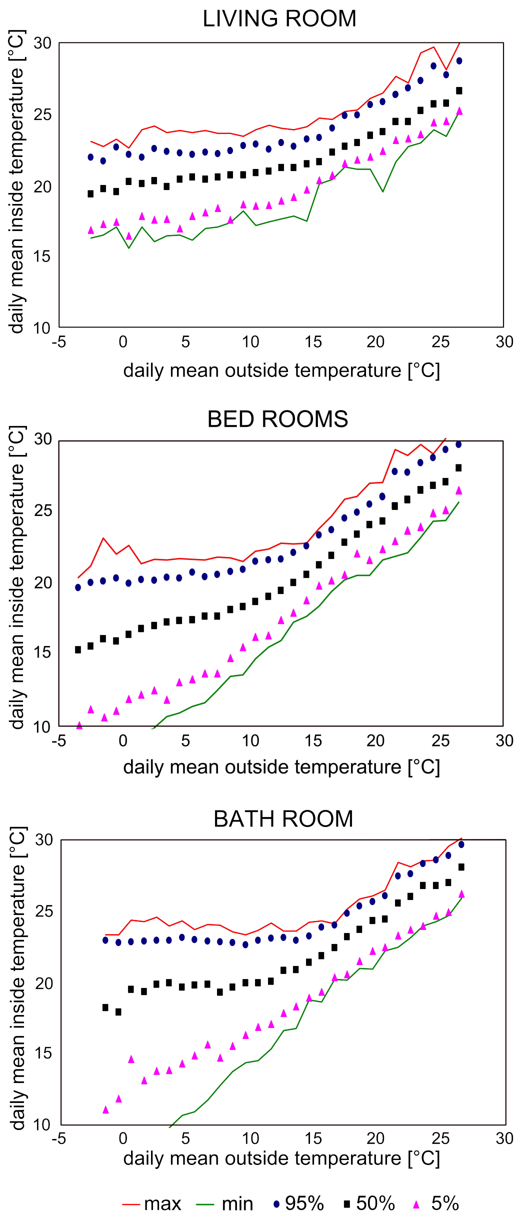


Figure 3.13: Daily average indoor temperature dependence on daily average outdoor temperature: minimum, maximum, 95-, 50- (median) and 5-percentiles. Source: Janssens and Vandepitte (2006).

Given the overview of the heating behaviour in the less inhabited parts of the dwelling, the following conclusions can be drawn:

- In order to be useful in any dynamic building simulation program, data should be available that can answer the twofold question: when are the less inhabited rooms heated and to which temperature? For now, no such data source is currently available.
- The global overview of the few data available suggests that bedrooms are only occasionally heated and that the heating behaviour in the bathrooms shows a large spread (heated versus completely unheated bathrooms).
- As Hunt and Gidman (1982) found a strong inter-room correlation, suggesting that temperatures in the rest of a home (apart from the living room) tended to follow each other closely, it

strengthens the assumption of considering a dwelling as a two-zone building: one zone heated to comfort temperatures (living rooms, kitchen, bathroom) and one zone rarely or never heated (bedrooms, hallway, etc.).

Implemented model

Based on the above findings, the final building model (see Chapter 4) will be considered as a 2-zone model: a day- and nightzone. The implementation of the heating preferences in the dayzone is already discussed in the previous section. The final implementation of the nightzone heating behaviour is as follows.

Based on the 17 % households who always heat all rooms following Leidelmeijer and Grieken (2005) and the 24 % households who report to heat the bedrooms during the day when someone is at home (TNS 2013), an estimation of 20 % is made representing those households who follow the same heating pattern both in day- and nightzone. The remaining 80 % of the households follow a more economic regime and never or only occasionally heat the nightzone. By lack of quantitative data, a further division of the latter group is done in a pragmatic way. On the one hand into those who take over the setback temperature from the dayzone but only during nighttime (20 % of all households) −they could be considered to switch the nightzone radiator valves to setback position when they go to sleep and switch them back off when they get up. On the other hand into those who never heat the nightzone (60 % of all households) −they keep all nightzone radiator valves at minimum temperature (T_{min}) position (see below).

For all households, it is assumed that they never allow the temperature to drop below T_{min}=10 °C. This however does not imply that nightzone temperatures cannot be lower than 10 °C. As said above (see 3.3.2), when the room thermostat is off, typically the case when the main living room has reached its desired temperature, no heat is available for the entire dwelling. This situation is also taken over in the simulations: as soon as the temperature in the dayzone reaches its set temperature, the ideal heating system is switched off and the nightzone temperatures can drop below 10 °C.

All the above is summarized in Table 3.10, with an example given in Table 3.11.

The lack of knowledge about the heating behaviour in the less inhabited part of the dwelling forces to make a considerable amount of assumptions. This is a serious drawback in the overall reliability of the behavioural model, since the less inhabited rooms can take up a significant spatial share of a dwelling, making their heating behaviour a substantial component in the overall energy use for space heating. To capture this, future research should put primary effort in gaining much more insight in the heating behaviour in rooms, other than the main living room.

Table 3.10: Overview of the different nightzone heating schedules, depending on the parameter PATTERNNIGHT and with the setback temperature defined as TSETPOINT − DELTAT (T_{min} = 10 °C).

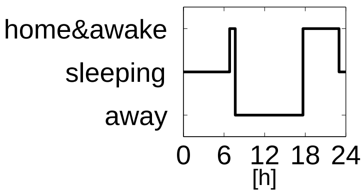
PATTERNNIGHT			**Temperature assigned during each state** home & awake	away	sleeping
1	always heated	20%	$T_{set,dayzone}$[a]	$T_{set,dayzone}$[a]	$T_{set,dayzone}$[a]
2	only during nighttime	20%	T_{min}	T_{min}	setback
3	never heated	60%	T_{min}	T_{min}	T_{min}

[a] see Table 3.7

Table 3.11: Example to illustrate assessment of heating schedule in nightzone (in complement with dayzone example in Table 3.8 on page 59).

Sampled parameters

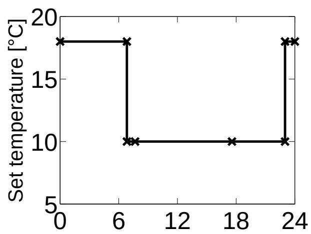
$PROFILE_{WEEK}$ =



WHENSETBACK	=	3
TSETPOINT	=	21.5 °C
DELTAT	=	3.5 °C
PATTERNNIGHT	=	2

➡

Implemented heating schedule NIGHTZONE



3.3.7 Ventilation preferences: window opening

Literature review

When discussing the ventilation preferences of inhabitants in this section, the scope will be limited to the manual control of opening/closing windows, mostly in dwellings where natural ventilation is applied. Apart from the fact that occupants tend to operate their mechanical exhaust ventilation system at much lower flow rates than prescribed (VITO et al. 2012b), no information could be found on if and how inhabitants interact with the settings of their ventilation system like manual adjustments of ventilation components or closing trickle vents.

From the main bulk of literature concerning the occupants' window opening behaviour, only a limited amount is applicable to residential buildings (e.g. Johnson and Long (2005), Andersen et al. (2009, 2013)). It is essential to point out the difference with the large share of studies relying on measurements in office buildings (e.g. Roetzel et al. (2010), Yun et al. (2009), Herkel et al. (2008), as the user behaviour regarding opening windows can be substantially different in both type of buildings. Unlike dwelling inhabitants, employees in an office environment do not have to consider possible financial consequences of opening windows; the energy bills are paid by someone else. As a result, window opening during wintertime will be much less limited by any energy-awareness in office buildings than it will be in residential buildings.

The majority of papers concerning window opening in a residential context have been recently reviewed by Fabi et al. (2012). Their literature review highlights that "*what seems to be a simple task, to open or close windows, is in reality a task that is influenced by many factors, which interact in complex ways*". The most frequently cited study, the study of the IEA - EBCS Annex 8, dates back to 1988 (Dubrul 1988) and gathered both questionnaires and measurements with respect to residential ventilation in Belgium, Germany, Switzerland, the Netherlands and the United Kingdom. According to their study, the zones mainly vented are bedrooms, while the greatest percentages of windows never opened are in living rooms, kitchens and bathrooms. This finding is consistent with the findings of Erhorn (1988) in 24 identical flats in Germany, where it was also seen that windows were open longest in summer (about 25 % of time) and shortest in winter (only 5 % of time). Dubrul (1988) also found that the maximum of window openings occurs in the morning. According to Keiding (2003) 51.3 % of a sample of Danish households slept with an open window during autumn while 25 % had a window open during the night in winter time. They also found that 91.5 % of the respondents vented by opening one or more windows each day throughout the year. The research of Erhorn et al. (2001) based on German field investigations, shows that the use of windows is limited in winter to about 1-2 hours a day and that the frequency of opening windows stays the same independent of the type of ventilation system installed (natural or mechanical). In a recent study on the user behaviour of 33 households during winter Delghust et al. (2012) found a very low amount of open window daytime probabilities in the living room (less than 8 %) and only slightly higher daytime probabilities of open windows in the bedrooms, yet not during times of presence.

When looking for drivers for the window opening behaviour, only little consensus is found. In the study of IEA - EBCS Annex 8 (Dubrul 1988), the type of dwelling, orientation and type of the room are the main parameters found to have an influence on the window opening and closing. Time of the day was found to determine the transition probabilities (closed open and open to closed) in the study of Johnson and Long (2005). Also the outdoor temperature has proven to have a considerable impact on the window opening behaviour (Erhorn 1988, Dubrul 1988, Andersen 2009, Andersen et al. 2013). Both Erhorn (1988) and Dubrul (1988) found a significant decrease in the prevalence of open windows at high wind speeds. The latter even found that nearly all windows were closed at wind speeds above 8 m/s.

Implemented model

Despite the available studies, there still is a lack of understanding in the relationship between indoor air quality and the window opening behaviour of occupants (Fabi et al. 2012). Also, the window opening behaviour in residential dwelling is not yet studied in the same extent as it is for office buildings. A probabilistic window opening and closing model for residential use is recently developed by Andersen et al. (2013). However, it is based on 8 month measurements in only 15 Danish dwellings. This is a rather low sample for the developed high-resolution model (10 minutes time step), undermining its representativeness and reliability. In addition, it is one thing to predict when windows are open/closed, it is another thing to correctly translate the effect of that action into the building energy simulation environment. Due to calculation time constraints, air flows will not be modelled in detail in the building energy simulations of this research work. As such, the window opening behaviour will be incorporated in a simplified way.

The implementation is based on direct measurements of the air flow rate due to window opening in 14 naturally ventilated Danish dwellings (performed by Kvisgaard (1985), data taken over from the IEA - EBCS Annex 8 (Dubrul 1988)). The measurements were carried out during wintertime, making the results applicable to the heating season period, which is the focus of this present research work. The constant concentration tracer gas technique was used to continuously measure the overall air change rate, typically over a period of one week. By repeating the measurements in an unoccupied period, the effect of the window opening on the overall air change rates could be separated. The resulting distribution in time-averaged air change rates due to window opening is given in Figure 3.14. Even though only 14 data points are available, a very satisfying lognormal fit could be made.

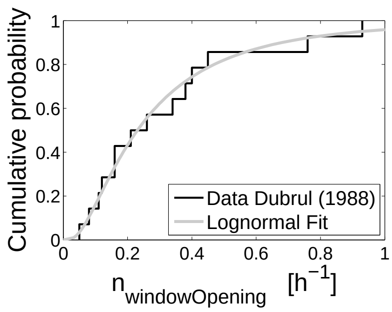


Figure 3.14: Empirical and fitted cumulative distribution of the measured mean air change rate due to window and door opening. Source of datapoints: Kvisgaard (1985), distracted from Dubrul (1988).
μ_{sample} *= 0.315* h^{-1} *;* σ_{sample} *= 0.26* h^{-1} *; fit ~* LogN*(-1.46 ; 0.84)*

Although executed a long time ago, the data of Dubrul (1988) still correspond quite well with more recent findings. Also in Denmark, Bekö et al. (2011) measured the CO_2-concentration in 500 children's bedrooms during the nights from March until May 2008 and used these CO_2-concentrations to calculate bedroom air change rates (including airflows both from outdoors through air leakage and window opening and from adjacent spaces). The calculated air change rates were also lognormally distributed, with a median value of 0.43 h^{-1} and a sample mean of 0.62 h^{-1}. Although these values are not entirely comparable to those of Dubrul (1988) (calculated instead of measured values, only bedrooms instead of total dwelling air change rates), the order of magnitude is remarkably similar. As expected the values of Bekö et al. (2011) are higher because they derived the total airflow −and not only the window opening airflow− and because the measurements are performed in spring instead of winter (window opening is more likely when outdoor temperatures are higher (Erhorn 1988, Dubrul 1988, Andersen 2009, Andersen et al. 2013))).

Yet, an important remark must be made when using the data of Dubrul (1988). In the IEA - EBCS Annex 8 report (Dubrul 1988), it was indicated how the above sample of Danish and naturally ventilated dwellings "*probably was substantially more airtight than those found in most countries participating in this annex*". In airtight dwellings without mechanical ventilation system more intense window opening behaviour is quite likely compared to air leaky dwellings, where in- and exfiltration can already take up a significant share of the necessary air change rate. As the latter dwellings form the main focus of this research work, it must be kept in mind that the above air change rates are to be seen as upper limits and possibly an overestimation of actual window opening air change rates in average Belgian dwellings.

When using the lognormal fit of Figure 3.14 in the behavioural model, the distribution is cut-off at 2 h^{-1} to avoid unrealistically high air change rates. Also, the air change rate $n_{windowOpening}$ applies to the whole dwelling, whereas the previous literature review clearly showed how, during wintertime, the rooms mainly vented are the bedrooms, in contrast with the living rooms where almost no open windows were traced. Therefore, it is decided to impose the total air flow $\dot{V}_{win} = n_{windowOpening} \times V_i$ only in the nightzone, leading to a nightzone air change rate of

$$n_{windowOpening,NIGHT} = \frac{\dot{V}_{win}}{V_{i,NIGHT}} = \frac{n_{windowOpening} \times V_i}{V_{i,NIGHT}} \qquad [h^{-1}] \tag{3.5}$$

with V_i and $V_{i,NIGHT}$ the interior volume of the total dwelling and nightzone respectively [m^3]. As said, no window opening behaviour is modelled in the dayzone, so $n_{windowOpening,DAY} = 0$.

3.3.8 Use of appliances

The use of appliances has a double effect on the overall energy demand profile of a dwelling (Page 2007). On the one hand, it is an important source of electricity use and peak load of the electrical grid. On the other hand, it is an indirect source of casual heat gains to the zones of the building. In the electrical research field, high-resolution time-series models are available that stochastically generate appliance related occupant behaviour (switching ON/OF appliances), often based on large-scale measurements of real-life appliance use and combined with occupant presence models (Page 2007, Widén and Wäckelgård 2010, Tanimoto and Hagishima 2010). These models are mainly used for the first aspect of realistic appliance use patterns, because an appliance being ON or OF can be directly linked to an electric power demand and thus, an overall dwelling electricity demand profile can be generated.

In this work, the use of appliances is only included for the second effect, being its share into the total internal heat gains and thus, its contribution to a lower demand for space heating. For this aim, the high-resolution stochastic models are quite an overkill. In general, internal gains are less of a benefit in single-family buildings because of the smaller amount of internal gains per conditioned building area compared to office buildings. Also, in order to use these detailed models for the generation of more realistic internal gains, it is still necessary to link the state of every separate appliance to an expected heat dissipation power: which amount of (latent/sensible) heat is dissipated when a dishwasher is in use, when a TV is switched on, when a laptop is put in standby-modus etc. Many assumptions are to be made and unfortunately, reliable and precise information on the dissipated heat of different equipment types is difficult to find.

Implemented model

It is therefore decided to not model the internal heat gains for each of the appliances separately. Instead, all possible sources of internal heat gains (occupants, lighting and use of appliances) are treated together in a simplified model, largely based on the default heat gain levels as found in Annex G of the standard ISO/FDIS 13790 (2007). In the latter, different default levels of internal heat gains, expressed in W/m^2 floor area, are given depending on the type of rooms and the time of day, as can be seen in Table 3.12.

Table 3.12: Heat flow rate from occupants and appliances; default values in the absence of national values. Source: ISO/FDIS 13790 (2007)

	Heat flow rate in W/m^2		
	7-17h	**17-23h**	**23-7h**
Living room + kitchen	8	20	2
Other conditioned areas (e.g. bedrooms)	1[a]	1[b]	6

[a]Increasing to 2 W/m^2 on weekenddays
[b]Increasing to 4 W/m^2 on weekenddays

This overall procedure is taken over in the behavioural model, yet with some adaptations:

- Instead of using fixed time periods, the occupancy profiles from Section 3.3.1 are used. Depending on the activity state, different heat gain levels are assigned following Table 3.13.
- Analogously as in ISO/FDIS 13790 (2007), a distinction is made in the main living rooms between a high level of gains, $QGAIN_{DAY,HIGH}$, during typical cooking hours (here 17-21h is chosen) and an intermediate level, $QGAIN_{DAY,INTERM}$, otherwise. The high level is of course only imposed when it coincides with the state 'home and awake'.
- Three heat gain levels are expressed stochastically to allow for a large ranger in possible values:
  - $QGAIN_{DAY,HIGH}$ ~U(14;20) W/m^2 (uniform distribution)
  - $QGAIN_{DAY,INTERM}$ ~U(6;10) W/m^2(uniform distribution)
  - $QGAIN_{NIGHT,HIGH}$ = 90 W per person × NUMOCC with NUMOCC the stochastic amount of occupants (see further section 3.4.2)

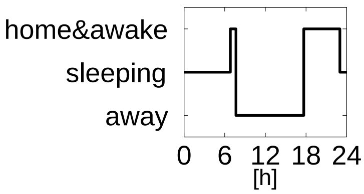
An example is shown in Table 3.14. All heat gains are modelled as being dissipated 50 % by longwave radiation and 50 % by convection.

Table 3.13: Overview of the different internal heat gain levels used in the behavioural model.

	Heat flow rate assigned during each state		
	home & awake	**away**	**sleeping**
DAYZONE	$QGAIN_{DAY,HIGH}$ (from 17-21h) $QGAIN_{DAY,INTERM}$ (else)	2 W/m^2	2 W/m^2
NIGHTZONE	1 W/m^2	1 W/m^2	$QGAIN_{NIGHT,HIGH}$

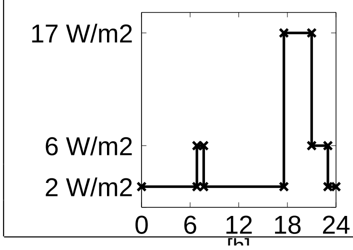
Table 3.14: Example to illustrate assessment of internal heat gains in day- and nightzone - for a nightzone floor area of 80 m^2.

Sampled parameters

$PROFILE_{WEEK}$	=	
$QGAIN_{DAY,HIGH}$	=	17
$QGAIN_{DAY,INTERM}$	=	6
$NUMOCC$	=	4

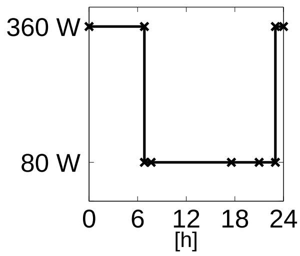
➡

Implemented heat gains DAYZONE



➡

Implemented heat gains NIGHTZONE



3.3.9 Conclusion

In the previous sections, each of the different user behaviour aspects, relevant for the scope of this research, has been discussed and submodels have been developed for implementation in the behavioural model. However, before all different submodels can be put together in the final behavioural model, it is necessary to analyse how and if each of these submodels are affected by external parameters like the household or building characteristics. If so, these influences should be incorporated in the model to enhance its overall reliability. This is done in the following section.

3.4 Drivers for user behaviour

As already explained at the beginning of this chapter, user behaviour actions are no stand-alone phenomena. Instead, they are driven by many different factors, called 'drivers'. Three categories are detected: household characteristics, building characteristics and outdoor climate. How each of the drivers relate to user behaviour and the final energy use for space heating, has already been shown schematically in Figure 3.1.

This section focuses on the actual relevance of these drivers and on whether they can be reliably implemented in the final behavioural model. For the latter purpose, two conditions should at least be fulfilled. Firstly, the link between the drivers and the user actions should be given in a quantitative way. There is little use in studies that give their results only qualitatively, like 'the occupant is more likely to ...'. What is needed are relationships expressed in terms of partial correlations, as these can be part of a correlation matrix C, directly implementable in the correlated sampling scheme (see section 3.2.2). Secondly, if quantitative data is available, it is preferably based on the same and sufficiently large household sample in order to develop a consistent set of relationships.

A literature review is performed first. The available information does not identify many relevant drivers and proves to be scattered over many different studies. To account for the latter, it is decided to perform our own analysis on the large Belgian Energy Consumption Survey (ECS), mentioned already several times in the previous paragraphs. This rich database contains both household, behavioural and building characteristics from the same population of 3396 Belgian households, allowing to deduce the required consistent set of correlations.

3.4.1 Literature review

Household characteristics

Age has proven to be an important sociological driver for the heating behaviour of the occupants: elderly people are more likely to heat to higher temperatures (Leidelmeijer and Grieken 2005, Oreszczyn et al. 2006, Andersen et al. 2009, Kelly et al. 2013) and heat for more hours (Guerra Santin and Itard 2010). Kane et al. (2010) also found indications that older occupants set higher living room temperatures but lower bedroom temperatures while younger occupants have more uniform demand temperatures. Of course, the latter is not necessarily an indication of a purely sociological preference, driven only by age, but is probably also linked to elderly people living more in older dwellings with poorer heating systems (see e.g. ECS-database section 3.4.2).

The impact of *household size* on the heating preferences is less clear: Guerra Santin and Itard (2010) found no relationship between household size and winter thermostat settings, while Conner and Lucas (1990) reported a smaller number of setbacks for higher number of occupants.

Quite obviously, the *employment status* is strongly linked to the occupancy periods and heating time schedules (Delghust et al. 2013). Indeed, the analysis of the occupancy profiles of Aerts et al. (2014) (see section 3.3.1) revealed strong correlations between the occupancy profile and socio-economic characteristics: the higher the age of the head of the household ($\rho = +.42, p < .001$) and the lower its income ($\rho = -.26, p < .001$) and activity level ($\rho = -.54, p < .001$), the more likely that he/she falls under the high profile numbers (most hours home and awake).

Finally, also the household *income* might be a driver for heating behaviour, as the household income determines how much money can be spent on the monthly energy bill and on (energy efficient) building and heating system investments, which directly induces more or less economic heating behaviour (Kelly et al. 2013). Yet, no strict evidence is found for that. Guerra Santin et al. (2009) analysed survey data from 15 000 Dutch households and found only small negative partial correlations between reported temperature during the evening and income ($r = -.046, p < .001$) and between the temperature setting during the day with income ($r = -.138, p < .001$). In other studies, the income did not show to have any impact on the occupant's behaviour (Vine 1986, Guerra Santin and Itard 2010).

Rather surprisingly, no strong evidence is found in the literature for a clear link between household characteristics and their user behaviour actions. Apart from the influence of age on the temperature setting and the employment status on the occupancy and heating periods, no other influencing household characteristics are identified.

Building characteristics

When looking at the influence of building characteristics on the heating preferences, the recent review of Wei et al. (2014) provides a considerable amount of studies that, to a greater or lesser extent, prove the influence of building characteristics on the occupant heating behaviour. Nevertheless, not all studies mentioned by them are equally reliable in their conclusions as many of them are based on measured indoor temperatures, which is a questionable method when one is interested in the heating preferences themselves (setpoints, application of setback, heating the bedrooms etc.) As such, only a selection of reliable studies is given here.

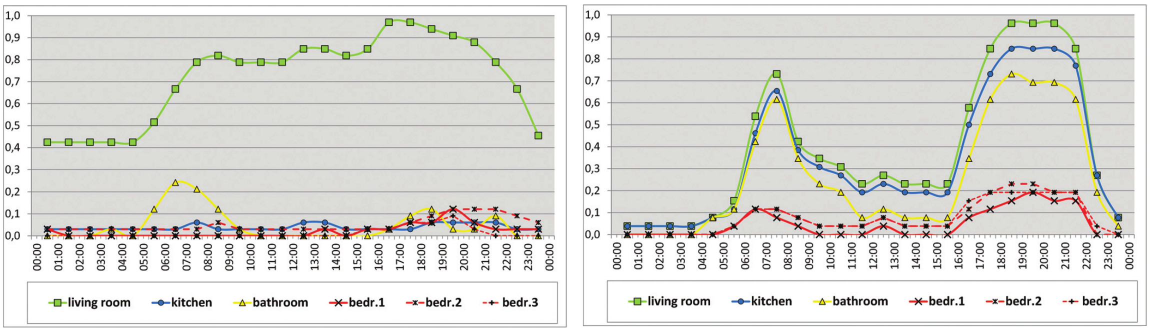
Concerning the *dwelling type*, the review of Vine (1986) found lower winter thermostat settings among multi-family homes in five US surveys, while two other studies found no differences. Based on data collected from 600 Swedish households, Linden et al. (2006) state that households living in detached houses have to a great extent adopted a lower setpoint temperature than households living in apartments. Yet, no quantitative evidence is provided for this statement. The DEFRA (Department for Environment, Food & Rural Affairs in the UK) carried out a survey regarding thermostat settings, in which people living in flats also reported higher settings than those living in detached houses (NHBC (2012) cited by Wei et al. (2014)).

In contrast with the dwelling type, no evidence is found that *dwelling age or size* have a significant impact on the heating preferences. Concerning the age however, this lack of evidence can possible be explained by the fact that many studies only focus on a particular part of the housing stock, thereby not covering the full range from old to new dwellings.

Only scattered evidence was found that the heating behaviour is driven by the *insulation level* of the house. For example, Guerra Santin et al. (2009) found that thermal quality has only limited influence on the temperature settings in a sample of 15 000 Dutch dwellings. This is not as expected, because it is typically assumed that people living in badly insulated dwellings show a more economic heating behaviour than people in well insulated dwellings. This lack of evidence could be explained by the fact that typically only the rather invariant heating set-point in the main room (Shipworth 2011) is included in the analysis, instead of also other more sensitive heating variables like the amount of setback and the heating behaviour in bedrooms, hallways, etc. Studies that do include these variables are however rather scarce: only two such studies have been found.

In the work of Leidelmeijer and Grieken (2005), the (invariant) temperature settings were only related to the household characteristics, while the patterns defining which rooms were heated or not, were related to both the household and building characteristics. Unfortunately, no qualitative data supporting this statement were given. Similarly, Delghust (2014) found different daytime probabilities of the heating being on for an old and a new neighbourhood (see Figure 3.15), suggesting that the household and building characteristics (amongst which also the availability of heating systems) indeed play a role in the heating behaviour. Based on a large-scale measurement campaign in two neighbourhoods, Delghust et al. (2013) derived hourly probabilities that the heating was on for different rooms - see Figure 3.15. The probabilities illustrate the complexity of how both household and building characteristics impact heating behaviour. In the old neighbourhood (built in the 1960s and owned by a social housing company) the households are much more likely to be at home during the day. Also, as these dwellings are mainly heated by a single gas furnace in the living room and only have small additional (expensive) electrical heaters in the bathroom and bedrooms, only the living room is consistently heated with the remaining part of the dwelling barely heated. In the recent neighbourhood (built according to the current energy standards, with central hydronic heating and inhabited by private owners), the probabilities reflect the higher employment rate of the households: during the day, people are more likely to be at work so the heating is switched off. During hours of presence however, the probabilities of the heating being on in rooms other than the living room are much higher. Interestingly, even though the better thermal performance of the newly built neighbourhood should minimize the need for heating the bedrooms, the opposite is observed: higher bedroom probabilities in the new neighbourhood compared to the old neighbourhood. A combination of factors could explain this: the aforementioned presence of local (and expensive electrical) heaters in the old neighbourhood, the difference in income between the two groups of households and also the rebound effect (Sorrell et al. 2009), being the fact that inhabitants tend to behave less economically as soon as heating costs drop –see also 2.4.1.

Even though the above studies of Leidelmeijer and Grieken (2005) and Delghust (2014) give a convincing indication that both the household and building (both insulation level and heating equipment) characteristics influence how people heat their dwelling, in particular the less inhabited parts of it, it is difficult to translate this knowledge into the behavioural model. To do so, quantitative fig-



(a) (b)

Figure 3.15: Probability of heating being on during a weekday for (a) the old neighbourhood and (b) the new neighbourhood, in the living room (green), kitchen (blue), bathroom (yellow) and sleeping rooms (red). Source: Delghust (2014)

ures should be available, preferably by means of correlation coefficients. Unfortunately, this is not the case.

Additional figures are found for the *dwelling heating equipment*. Hunt and Gidman (1982) reported that dwelling mean temperatures of centrally heated houses were about 3 °C higher than of non-centrally heated houses. In the research from Kavgic et al. (2011), the mean living room and bedroom temperatures in houses with district heating were 2.3 °C and 3.0 °C higher respectively than dwellings with individual central heating. The reason was both technical, as the occupants could not directly regulate the heat supplied by the radiators, but also economical, as the heating costs were only determined per square meter of living area, eliminating all financial incentives to reduce heating demand. In the analysis of the Belgian ECS-database (see section 3.4.2) the households with floor heating applied no setback more often (13 %) than the households with the conventional convectors/radiators (9 %). Due to the larger inertia of the floor heating emission systems, this is as expected. However, with the floor heating households making up only 47 of the total sample of 3396 households, it is diffult to draw any robust conclusion.

Especially the type of *temperature control* is frequently identified as a driver, yet with varying conclusions regarding its causal effect. A survey in 299 US households (Nevius and Pigg 2000) suggests that households with programmable thermostats are much more likely to apply any form of setback both during night and during day (also found by Tachibana (2010)) and to apply slightly higher settings during the day when someone is at home. Both findings are in contrast with the conclusions of Jeeninga et al. (2001). In this study a questionnaire was carried out in 180 Dutch households, revealing that households with an analogue thermostat tended to more often lower the temperature when absent for a longer period, while the set-points themselves were not influenced by the type of thermostat. Guerra Santin and Itard (2010) analysed 2 Dutch surveys and found that households with a programmable thermostat were associated with higher temperature settings during the night in one survey, and with more hours with radiators on in the other survey. Many other conclusions and studies concerning the type of temperature control could be found (see also review Wei et al. (2014)), but they only add to the global trend that, depending on the study, different outcomes were found on how temperature control influenced the behaviour.

Although one expects that the building and its equipment impact the way occupants heat their homes, only weak and fragmented empirical evidence is found for this in the literature.

Outdoor climate

The impact of outdoor climate on user behaviour has been evaluated in different existing studies. Concerning the heating preferences, the reviewing work of 53 studies by Vine (1986) found only one study in which it was found that homes in warmer climates turned the heater off and maintained lower winter settings than homes located in other climates. Based on the measurements of the set-points of thermostatic radiator valves (TRV) in 13 Danish dwellings, Andersen et al. (2011)

concludes that "*the outdoor temperature, solar radiation and outdoor relative humidity were negatively correlated with the TRV set-point indicating that the heating set-point was increased when these variables decreased*". Yet, the sample analysed is small and the linear regression model had a weak explanatory power ($R^2 = 0.31$), so even though proposed by the authors, care must be taken in using this regression model in building energy simulation models.

Overall no strong empirical evidence is found for relevant influences of the outdoor climate on the thermostat settings of a household.

Link between household and building characteristics

As visible on Figure 3.1, there is also an expected link between household and building characteristics, which does not directly affect the user behaviour, but which might be an important aspect in modelling user behaviour on a aggregated level. For example, homes owned by a social housing company are more likely to be occupied by households with limited income levels and/or unemployed status. It might be more appropriate for the housing company to use adapted behavioural profiles, fitting with these household characteristics, rather than general profiles.

Evidence for these correlations between household and building variables is found in Guerra Santin et al. (2009). In her analysis of 313 households, positive medium partial correlations were found between household size and number of rooms ($r = .424, p < .001$) and household size and useful living area ($r = .330, p < .001$), suggesting that large households are associated with larger dwellings. Also the influence of income was found to have a positive medium correlation with useful living area ($r = .345, p < .001$), suggesting that households with larger incomes have larger dwellings than lower-income households. The latter is also concluded by Leidelmeijer and Grieken (2005), based on the cluster analysis of the KWR database containing 15 000 Dutch households.

Apart from these studies, no other clear figures or evidence could be found concerning the link between household and building characteristics.

Conclusions literature review

Although one can easily and intuitively explain the relationships between drivers and user behaviour actions as shown in Figure 3.1, it is less straightforward to find quantitative evidence for this in the literature. Concerning the household characteristics, the age of the occupants seemed to significantly impact the setpoint temperature, while the employment status is correlated to the occupancy periods and its subsequent heating schedules. Concerning the building characteristics, only the temperature control proved to have a significant effect, yet the evidence found was contradictory in its conclusions. The outdoor climate proved to have no significant influence on the thermostat settings.

Nevertheless, the lack of evidence for strong influencing drivers does not necessarily mean they do not exist. It should also be seen as an indication for the huge complexity dealt with when trying to statistically detect the drivers. Different reasons are found for that.

At first, both drivers and user behaviour actions should be true indicators of what is to be analysed. As people tend to keep the thermal comfort in the living room to a descent level, whatever the consequences for the thermal comfort in the rest of the dwelling, the heating set-point alone is possibly a very poor indicator for heating preferences. Two studies were found that also take other variables into account (Leidelmeijer and Grieken 2005, Delghust 2014). They give a strong indication that both household and building characteristics influence how people heat their dwelling, in particular the less inhabited parts of it. Unfortunately, these relations could not be quantified into correlation coefficients.

Secondly, the reality proves to be very complex and difficult to unveil in a statistically meaningful manner. For example, if the heating behaviour shows to be related to the occupancy and occupancy is related to the employment status, then the heating behaviour will also be statistically influenced by the income, but also by the age (the older the occupant, the less likely to exert a job). By consequence, there is also a link between heating behaviour and education level (the higher the education level, the more likely a higher income is). It is clear how quickly a non-transparent clew of intercorrelations can be found, in which it is very difficult to reveal what is the true cause and what is more or less 'coincidentally' related to that (Leidelmeijer and Grieken 2005).

3.4.2 Drivers in the Belgian ECS-database

The literature review showed how many correlations are small, often based on non-Belgian populations and scattered amongst many different studies. However, in order to obtain a coherent set of correlation coefficients, they are all preferably based on the same set of households. To account for all this, it is decided to perform our own analysis on the large Belgian Energy Consumption Survey (ECS). This rich database contains both household, behavioural and building characteristics from the same population of 3396 Belgian households, allowing to deduce the required consistent set of correlations, applicable within the Belgian context.

To do so, the ECS-database and its variables are shortly described first, followed by the univariate analysis of the variables. Afterwards, the analysis of the correlation coefficients is discussed. All analyses are performed in `MATLAB R2013a` and its Statistics Toolbox.

Description of the ECS-database

The Energy Consumption Survey (ECS) for Belgian households (VITO et al. 2012a) was accomplished under the authority of EUROSTAT, a Directorate-General of the European Commission. The database was carried out from July until December 2011 and contains the energy survey results of 3396 households, already filtered for strange results and possible outliers. Weighting factors have been constructed to transform the final sample into a sample representative for the global household population. More details on the data processing and weighting procedure can be found in VITO et al. (2012a). In the following univariate analyses, both original and weighted results will be shown.

The sample size n per variable or any statistical hypothesis test is always based on the original, unweighted sample. This is necessary because the outcome of a hypothesis test is strongly influenced by the sample size: smaller sample sizes lead to more stringent criteria. Using the weighted sample means that the same data information is artificially enlarged, which is not desirable for interpreting statistical significance.

The questions and variables, retained from the ECS-database and used in this analysis, are listed in Table 3.15. The households were always able to tick the answer 'Do not know/No answer'. These answers have not been incorporated in the analysis.

NAME	*Question*	*Possible answers*
Household characteristics		
NUMOCC	Amount of occupants?	[1-13]
NUMKIDS	Amount of occupants <16 year?	[0 - 6]
AGECAT	Age category of head of the family	1 18 - 24 2 25 - 39 3 40 - 54 4 55 - 64 5 65+
ACTIVITY	Primary activity of the head of the family	1 Not working: retired 2 Not working: else 3 Working parttime 4 Working fulltime
INCOME	Level of monthly household income	1 less than 500 euro –> 7 3000 euro and more
User behaviour		
TSETPOINT	Tsetpoint in main room during day when someone is at home	[10 - 40] °C
WHENSETBACK	When do you lower the temperature in the dwelling?	1 Never 2 Only during day 3 Only during night 4 During night and when >3 hours away during day 5 During night and when <3 hours away during day
TSETBACK	Tsetback during night and when no one is at home (only when WHENSETBACK ≠ 1)	[10 - 40] °C
DELTAT	= TSETPOINT - TSETBACK (only when WHENSETBACK ≠ 1)	[0-20] °C
BATHS	How many baths for total family (weekly average)?	[0-70]
SHOWERS	How many showers for total family (weekly average) ?	[0-70]
SHOWERMIN	Average shower duration (only when SHOWERS ≠ 0)	1 ≤ 5 min 2 > 5 min and ≤ 10 min 3 > 10 min and ≤ 15 min 4 > 15 min and ≤ 20 min 5 > 20 min
Building characteristics		
YEARBUI	Year of construction	1 < 1921 2 1921-1945 3 1946-1960 4 1961-1970 5 1971-1980 6 1981-1990 7 1991-2000

Table 3.15: Variables from the ECS-database.

NAME	*Question*	*Possible answers*
		8 2001-2007 9 >2007
TYPEBUI	Type of dwelling	1 Free-standing 2 Semi-detached 3 Terraced 4 Flat
FLOORM2	Floor area of all levels	[0-3000] m^2
%FLOORHEAT	Percentage floor area heated	[0-1]
GLAZING	Main type of glazing	1 single glazing 2 double glazing 3 high efficiency double/triple glazing
INSROOF INSFLOOR INSWALL	Presence of insulation in (roof/floor/wall)	1 No () insulation 2 Part of dwelling has () insulation 3 Complete dwelling has () insulation
THICKINSROOF	Thickness of roof insulation (if present)	1 d ≤ 5 cm 2 5 cm < d ≤ 10 cm 3 10 cm < d ≤ 15 cm 4 15 cm < d ≤ 20 cm 5 d > 20 cm
TYPEHEATING	Type of main heating system	1 Individual central heating system 2 Collective central heating system 3 Separate local heaters
AGEHEATER	From which period is (oldest) heat production unit in the dwelling? (only when TYPEHEATING = 1 or 3)	1 < 1960 2 1961 - 1970 3 1971 - 1980 4 1981 - 1990 5 1991 - 2000 6 2001 - 2006 7 > 2007
EFFBOILER	High efficiency label on gas/oil boiler? (only when TYPEHEATING = 1)	1 no 2 high efficiency boiler 3 condensing boiler
TYPEEMISS	Type of emission system (only when TYPEHEATING = 1 or 2)	1 floor heating 2 radiator/convector 3 air heating
VENTILATION	Which description fits the best with the ventilation system present in your dwelling?	1 no ventilation system 2 trickle ventilators either in windows or in kitchen/bathroom/toilet 3 mechanical exhaust system w/o heat recovery or heat pump extracting air from exhaust air

Table 3.15: Variables from the ECS-database (continued).

Univariate analysis of the ECS-variables

A short descriptive analysis is given of all variables separately (=univariate analysis) in order to get familiar with the database and its population. This will be done by showing their empirical frequency distributions.

Household characteristics The empirical frequency distribution of each of the household characteristics in the ECS-database is given in Figure 3.16, both for the original and the weighted sample. Note that the questionnaire is performed on the household level and that the household characteristics apply to the head of the households. This explains why the youngest age category (18 - 24 year) has a very low relative frequency, even in the weighted sample. This age category is mainly represented by young adolescents being more likely to be part of a household (with an older person being head of the household) rather than to have a household of themselves.

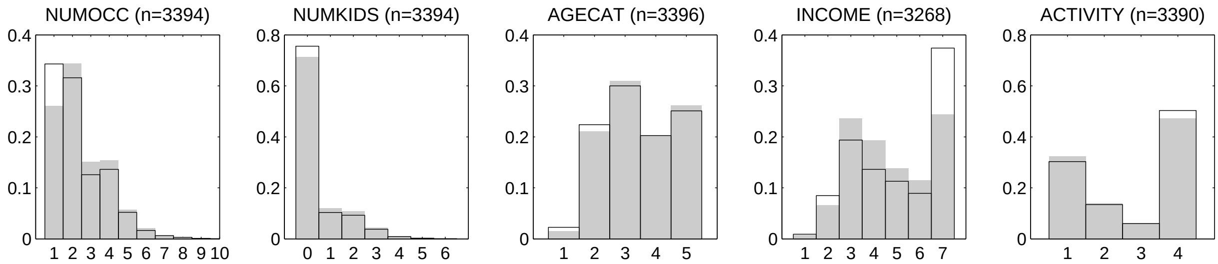


Figure 3.16: Empirical frequency distribution of the (head of the) household characteristics in the ECS-database. Grey filled: original sample - black lines: weighted sample. For the explanation of the x-axis: see Table 3.15.

User behaviour The six variables concerning the user behaviour on heating preferences and hot tapwater are shown in Figure 3.17. Less differences are found here between the original and weighted sample.

The variables TSETPOINT, WHENSETBACK and DELTA have already been discussed in section 3.3. Note that the frequency distribution of the amount of setback DELTAT is only based on those households who reported to apply setback (answers 2 to 5 under WHENSETBACK).

Although not within the scope of this research work, the user behavioural variables concerning the hot tapwater use are included in this analysis, as they might offer valuable information to other researchers. As can be seen, a large spread is observed in the weekly averaged amount of baths and showers. The main bulk of values is situated in the range of [0-10] baths per week and [0-20] showers per week. Also, more than 80 % of the households (who take a shower) report a shower duration of 10 minutes and less.

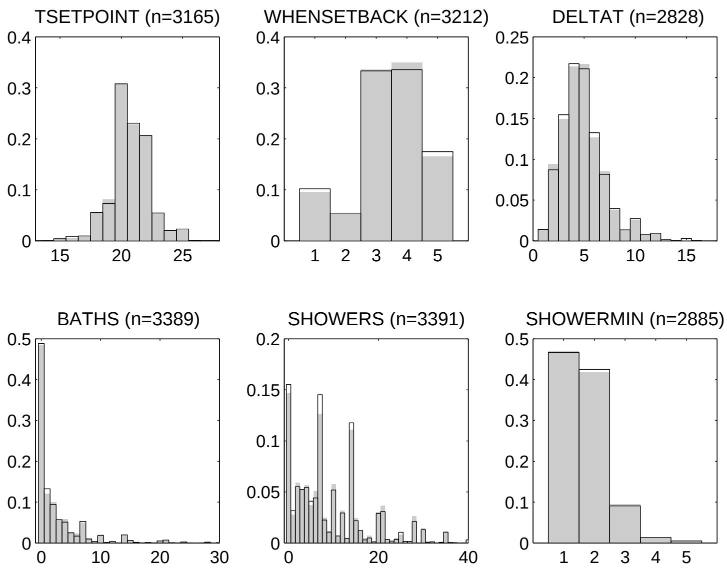


Figure 3.17: Empirical frequency distribution of the user behaviour variables in the ECS-database. Grey filled: original sample - black lines: weighted sample. For the explanation of the x-axis: see Table 3.15.

Building characteristics Figure 3.18 shows the empirical frequency distribution of each of the building characteristics. Here, almost no difference is observed between original and weighted sample.

The parameter FLOORM2 is calculated with the respondents best estimates of the 'floor area of ever floor level in the dwelling', without giving further rules to make these estimates. The parameter FLOORHEAT (percentage of floor area heated) is defined by asking the respondent 'to what degree every floor level is heated: not / one fourth / half / three fourth / entirely'. Hence, FLOORHEAT is not a pure building characteristic, but is also driven by the household preferences. Overall, both parameters should be seen as best, yet rough estimates of actual (heated) floor area and should therefore be handled with care.

It is important to note that, while the majority of the 3396 respondents is able to indicate the age category, type and floor area of the dwelling, a significant smaller part is able to indicate the presence of roof/floor/wall insulation. Almost all drop-out in answers is explained by the 840 households (= 25 % of original sample) living in flats. They are often unaware of the overall properties of the collective building and thus are forced to give a blank answer on these questions.

A similar downfall in answers is observed concerning the heating system variables. The overall type of heating system (central individual/collective or local) is generally well known by the households. Depending on this type of heating system, some questions were automatically skipped in the survey. For example, those who have a collective central heating system (TYPEHEATING = 2), have not been asked about the production side of the system (building period AGEHEATER or efficiency label of the central gas/oil boiler EFFBOILER). As all households with a collective central heating system turn out to live in flats and make up 43 % of all 840 households living in flats, the flat residents are strongly underrepresented in the samples of AGEHEATER and EFFBOILER. Also, those

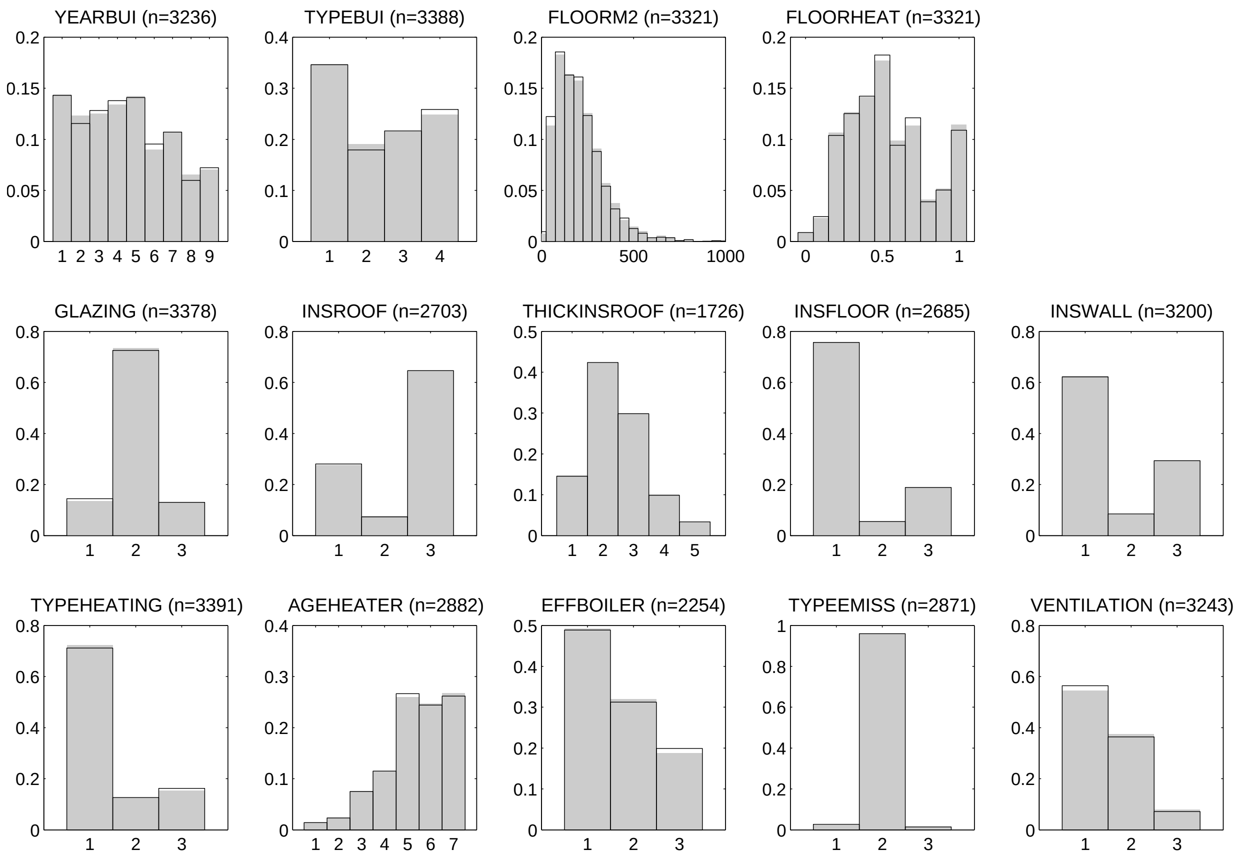


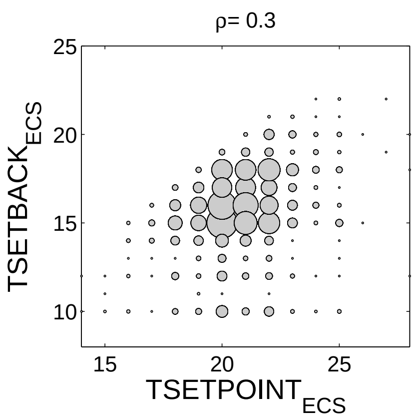
Figure 3.18: Empirical frequency distribution of the building characteristics in the ECS-database. Grey filled: original sample - black lines: weighted sample. For the explanation of the x-axis: see Table 3.15.

who use only local heaters (TYPEHEATING = 3, about 15 % of all 3396 households), did not have to specify the type of emission system (TYPEEMISS). Note that no information is included about the type of temperature control: manual or programmable thermostat, presence of external sensor, presence of thermostatic radiator valves. The survey did contain one question regarding the way the temperature could be controlled, but due to the ill-defined possible choices between which the respondents could choose, the overall answers are too blurred to be reliably used in this analysis.

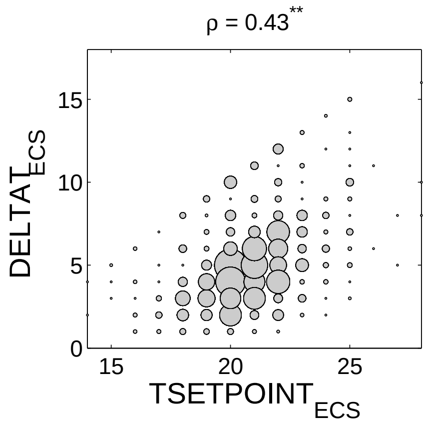
Analysis of the correlation coefficients

In this section, the mutual influence of each of the variables on other variables is analysed by means of Spearman's rank correlation coefficients (see section 3.2). This rather straightforward statistical technique is chosen here as it will allow a direct implementation of these correlations into the probabilistic behavioural model, compatible with the future Monte Carlo simulations based on correlated random numbers.

By means of illustration, the correlation between the setpoint temperature TSETPOINT and the amount of setback, TSETBACK, is shortly discussed here. The Spearman's rank correlation coefficients equals $\rho = 0.30$ (p-value < 0.001) and thus denotes a positive tendency: higher setpoint temperatures are associated with higher setback temperatures. This tendency is even more pronounced if, instead of TSETBACK, the temperature difference DELTAT = TSETPOINT - TSETBACK is correlated with TSETPOINT. In that case, an even higher coefficient of $\rho = 0.43$ (p-value < 0.001) is found. Therefore, it is this variable that will be taken over in the correlation matrix and the final behavioural model. All this is also made visible in Figure 3.19, showing the density scatterplots of TSETPOINT with TSETBACK and with DELTAT. Note that the survey asked for TSETPOINT and TSETBACK to be given as integers between [10 - 40] °C and that it logically dit not allow TSETBACK to be equal or higher than TSETPOINT. Due to the latter, the left upperpart of both scatterplots remains empty, so the positive correlations should not come as a surprise.



(a)



(b)

Figure 3.19: Density scatterplots between TESTPOINT and both TSETBACK (a) and DELTAT (b), calculated as TSETPOINT - TSETBACK (the sizes of the circles are proportional to the frequency of occurrence).

In Table 3.16 the Spearman's rank correlation coefficients between variable *i* and *j* are given. Every coefficient is based on those households who give a valid answer for both *i* and *j*, independently of their other answers. This means that a different set of households can be represented in different coefficients.

One might argue that it makes more sense in setting up a correlation matrix that is based on the same set of households, implying that all households who do not give a valid answer to each of the questions are omitted. Even though this indeed leads to a coherent correlation matrix, it does not necessarily lead to a representative matrix. By including only those households who gave valid answers on the relevant questions, the total sample size is strongly reduced to 1081 households: only cases with individual central heating are retained (necessary condition for answering on variable EFFBOILER) and almost all households living in flats are eliminated (unable to indicate the presence of insulation in roof/floor/wall - see above). Also, one ends up with those households who are well aware of the characteristics of their dwelling, risking that private owners, often living in larger and better insulated dwellings, are overrepresented. The analysis of the reduced sample (not shown here) indeed revealed how the reduced sample contains more households with a full-time working head of the household, living in large detached dwellings more frequently.

Table 3.16: Spearman's rank correlation coefficients between variable i and j - sample size different for every coefficient because depending on available answers per set of two variables.
(*) = correlation coefficient not significantly different from zero at the α = 0.001 level
(grey box) = correlation coefficient ≥ 0.20
([a]) = individual and collective central heating are taken together in category 'central heating' against the category 'local heaters'

	NUMOCC	NUMKIDS	AGECAT	INCOME	ACTIVITY	TSETPOINT	WHENSETBACK	DELTAT	YEARBUI	TYPEBUI	FLOORM2	%FLOORHEAT	GLAZING	INSROOF	THICKINSROOF	INSFLOOR	INSWALL	TYPEHEATING[a]	AGECATHEATER	EFFBOILER	TYPEEMISS	VENTILATION
NUMOCC	1	0.7	-0.34	0.51	0.4	*	*	*	0.08	-0.21	0.29	*	0.15	0.13	0.12	0.14	0.12	-0.1	0.1	*	*	0.06
NUMKIDS		1	-0.48	0.29	0.4	*	0.08	-0.08	0.06	*	0.1	0.09	0.09	0.06	0.12	0.1	0.07	-0.11	0.12	*	*	*
AGECAT			1	-0.25	-0.7	0.09	-0.13	0.08	-0.1	-0.13	0.12	-0.14	-0.09	-0.08	-0.15	-0.15	-0.08	0.08	-0.2	*	*	*
INCOME				1	0.48	*	0.12	-0.1	0.12	-0.31	0.41	*	0.24	0.26	0.17	0.2	0.22	-0.13	0.07	0.12	-0.07	*
ACTIVITY					1	-0.09	0.14	-0.08	0.12	*	0.08	0.07	0.13	0.12	0.15	0.17	0.16	-0.1	0.13	0.08	*	*
TSETPOINT						1	*	0.43	*	*	*	*	*	-0.07	*	*	*	0.09	*	*	*	*
WHENSETBACK							1	*	*	*	*	*	*	0.08	*	*	*	-0.1	*	*	*	*
DELTAT								1	*	*	*	-0.09	*	-0.07	*	*	*	0.12	-0.08	*	*	*
YEARBUI									1	-0.08	0.06	*	0.17	0.23	0.1	0.28	0.41	-0.14	*	*	*	0.13
TYPEBUI										1	-0.65	0.33	-0.12	-0.16	-0.09	-0.16	-0.22	*	0.12	*	*	0.07
FLOORM2											1	-0.36	0.15	0.14	0.15	0.15	0.22	-0.09	-0.09	*	*	*
%FLOORHEAT												1	*	0.07	*	*	*	-0.18	0.11	*	*	*
GLAZING													1	0.24	0.2	0.25	0.27	-0.13	0.13	0.21	-0.06	0.09
INSROOF														1	0.12	0.24	0.34	-0.14	0.07	0.11	*	0.08
THICKINSROOF															1	0.19	0.15	*	*	0.13	*	*
INSFLOOR																1	0.45	-0.1	0.07	0.14	-0.15	0.11
INSWALL																	1	-0.1	*	0.13	-0.09	0.09
TYPEHEATING[a]																		1	-0.08	*	*	-0.07
AGECATHEATER																			1	0.54	*	*
EFFBOILER																				1	-0.07	*
TYPEEMISS																					1	*
VENTILATION																						1

The main conclusions from Table 3.16 are given below. Many correlations, although statistically significant, are lower than 0.20. As this only suggests a rather weak association between the two variables, they are not considered as relevant relationships and are thus not discussed.

- **Many household characteristics strongly correlated to each other**
  The highest correlation coefficients of the total table are found between each of the household variables (left upper part of table). No strange results are seen here as they all follow the intuitive tendency that can be expected within a household. For example, the age category is strongly negatively correlated to both the number of occupants and number of kids (the older the inhabitants, the more likely the children left the house) and both income and activity (the older the inhabitants, the lower their income will be and the less likely it will be they go out to work). Also the income is positively correlated with the household size and activity level. When compared with the correlations between AGECAT, INCOME and ACTIVITY, as found in the Belgian Household Budget Survey (Aerts et al. 2013) and given in Table 3.2, a very statisfactory accordance is found, confirming the overall representativeness of both databases.

- **User behaviour variables practically uncorrelated to each other**
  When looking at the middle part of Table 3.16, it is remarkable how little the behavioural variables are linked to each other. Only one relevant and rather higher correlation is observed, being between the setpoint and the amount of setback (+0.43): the higher the thermostat setting when someone is present, the higher the setback setting (if applied) during night or when no one is at home (see also Figure 3.19).

- **Building characteristics strongly correlated to each other**
  It is no surprise that there is a large coherence amongst the different building properties (see right lower part of table). For instance, the more compact the dwelling typology (high values of TYPEBUI, corresponding mostly to appartments), the smaller the total floor area (-0.65 with FLOORM2). As expected, the presence of insulation in roof/floor/wall and the presence of better performing glazing are all quite strongly positively correlated with each other (+0.20 to +0.45). The insulation level of the wall is also quite strongly linked to the construction period of the dwelling (+0.41): the more recent the dwelling, the more likely that wall insulation is present.

  Concerning the heating system variables, there is the unsurprisingly strong correlation between the production year of the heater and its efficiency (+0.54): the more recent the boiler, the higher its efficiency. Also relevant correlations are found between the presence of insulating glazing and the efficiency of the boiler (+0.21). For the rest, no other relevant correlations are found for the heating system variables, neither with each other nor with the other building characteristics.

- **Household and building characteristics moderately correlated**
  The higher the income, the more likely to live in a detached dwellings (-0.31), the larger the total floor area (+0.41 which is close to the value of +0.345 found by Guerra Santin et al. (2009)) and the more likely that insulation of any kind is present (+0.20 to +0.26 with all insulations). This is as expected, because households with higher income can afford larger dwellings which are either new dwellings, in accordance with the present energy regulations, or either old dwellings which they can afford to retrofit in an energy efficient way. Also the age category is inversely linked with the age category of the boiler (-0.20): when people are older, they are less likely to have recent, more energy efficient boilers. Furthermore, the number of occupants reveals to be correlated to both the dwelling typology (-0.21) and the total floor area (+0.29), the latter again close to the value of +0.33 found by Guerra Santin et al. (2009), suggesting that larger households live more in detached dwellings with larger floor areas.

- **Heating preferences practically uncorrelated with other variables**
  Overall, there is no strong indication for a relation between the heating preferences and either household or building characteristics. There is some tendency for older households to apply setback less often (-0.13) and for households with higher levels of income and activity to apply setback more often (+0.12 and +0.14 respectively), yet the correlations are rather weak. The tendency for older occupants to set higher temperatures, as found by Leidelmeijer and Grieken (2005), Oreszczyn et al. (2006), Andersen et al. (2009), Kelly et al. (2013), is only slightly detected here (+0.09 between AGECAT and TSETPOINT). Very weak yet statistically significant correlations are found between the heating behaviour and some building characteristics. For instance, the more roof insulation is present, the more the households tend to adopt lower setpoints (-0.07) and apply setback more regularly (+0.08), but the less the temperature is lowered when applying setback (-0.07). Somewhat higher correlations are found with the type of heating system (TYPEHEATING): compared to households with central heating the households with local heaters set slightly higher setpoint temperatures (+0.09) and apply setback less often (-0.10), yet they lower the temperature more when setback is applied (+0.12). Interestingly and quite as expected, the households with central heating tend to heat a higher percentage of their dwellings than households with local heaters (-0.18 between %FLOORHEAT and TYPEHEATING). Overall though, based on the correlation coefficients found on this database, no clear evidence is found that a household's heating behaviour is strongly driven by it's size, income or age or by any specific dwelling characteristic.

3.4.3 Conclusion

The aim of the literature review and ECS-database analysis was to compose a set of relevant correlations, preferably based on the same set of households and applicable within the Belgian context. Two conclusions can be drawn.

Firstly, the trends found in the ECS-database correspond quite well with the findings from the literature review. The main conclusion is that *the heating behaviour actions seem to be only weakly influenced by either household or building characteristics*. Again, some reservations must be made. As already stated in the literature review, it is possible that the 'wrong' heating behaviour indicators are used here. Also in this database, the heating behaviour is only reflected in what happens in the main living room, while the total heating behaviour covers a much wider range of (unknown) actions, certainly in the less inhabited parts of the dwelling. Also, the database offered only limitedly useful information about the type of temperature control. This parameter proved to have some influence on the thermostat settings, even though the conclusions of the different studies were contradictory.

Secondly, one should argue that, when aiming for an objective observation of the rebound effect −in which inhabitants tend to behave less economically after an energy efficient retrofit− focus must be put on how the less inhabited parts of dwellings are heated. While the heating behaviour in the main living room proves to be rather invariant and unaffected by building characteristics like the insulation level, opposite indications are found in two studies regarding how the rest of the dwelling is (not) heated (Leidelmeijer and Grieken 2005, Delghust 2014). Unfortunately, no quantitative figures like correlation coefficients could be deduced. Hence, awaiting future research concerning the link between building characteristics and heating behaviour in rooms other than the main living rooms, possibly leading to relevant correlations between both, the rebound effect cannot be incorporated in the behavioural model.

Overall, although no predominant drivers for the heating behaviour could be identified, the above analysis still proves to be worthwhile in the development of a more consistent probabilistic behavioural model. The analysis revealed a quite strong correlation between TSETPOINT and DELTAT (+0.43). Also, DELTAT and WHENSETBACK proved to be weakly (<0.14) correlated to four household characteristics (NUMOCC, AGECAT, INCOME and ACTIVITY). Hence, it is useful to integrate these household characteristics in the behavioural model, as the four of them together might form a fairly good 'driver-combination' for when setback is applied. As AGECAT and ACTIVITY will now be sampled anyway, their correlations with TSETPOINT might as well be integrated. This leads to the final correlation matrix C, given in Table 3.18 (further below).

3.5 Final implemented behavioural model

Based on the previous literature work and analysis performed on the ECS-database, the final probabilistic behavioural model can now be presented. This final model is only applicable to the heating preferences, total internal heat gains (occupants, appliances and lighting) and the window opening behaviour. Cooling preferences, the detailed use of appliances and the use of hot tapwater are not considered. The implementation of the model is done in `MATLAB R2013a`.

3.5.1 Overview

The model consists of 3 elements: (i) the global framework describing how the heating preferences and internal gains are distributed in time and space, (ii) the probabilistic input distributions and (iii) the correlation matrix *C*.

Global framework

The global framework is represented schematically in Figure 3.20. As already stated above (see 3.3.2), this framework is strongly based on the predominant heating system in Belgium, being a hydronic central heating system with radiators and/or convectors (with regular and thermostatic valves in day- and nightzone respectively) and regulated by means of a programmable on/off room thermostat in the dayzone. Hence, the behavioural model starts with the determination of the occupancy

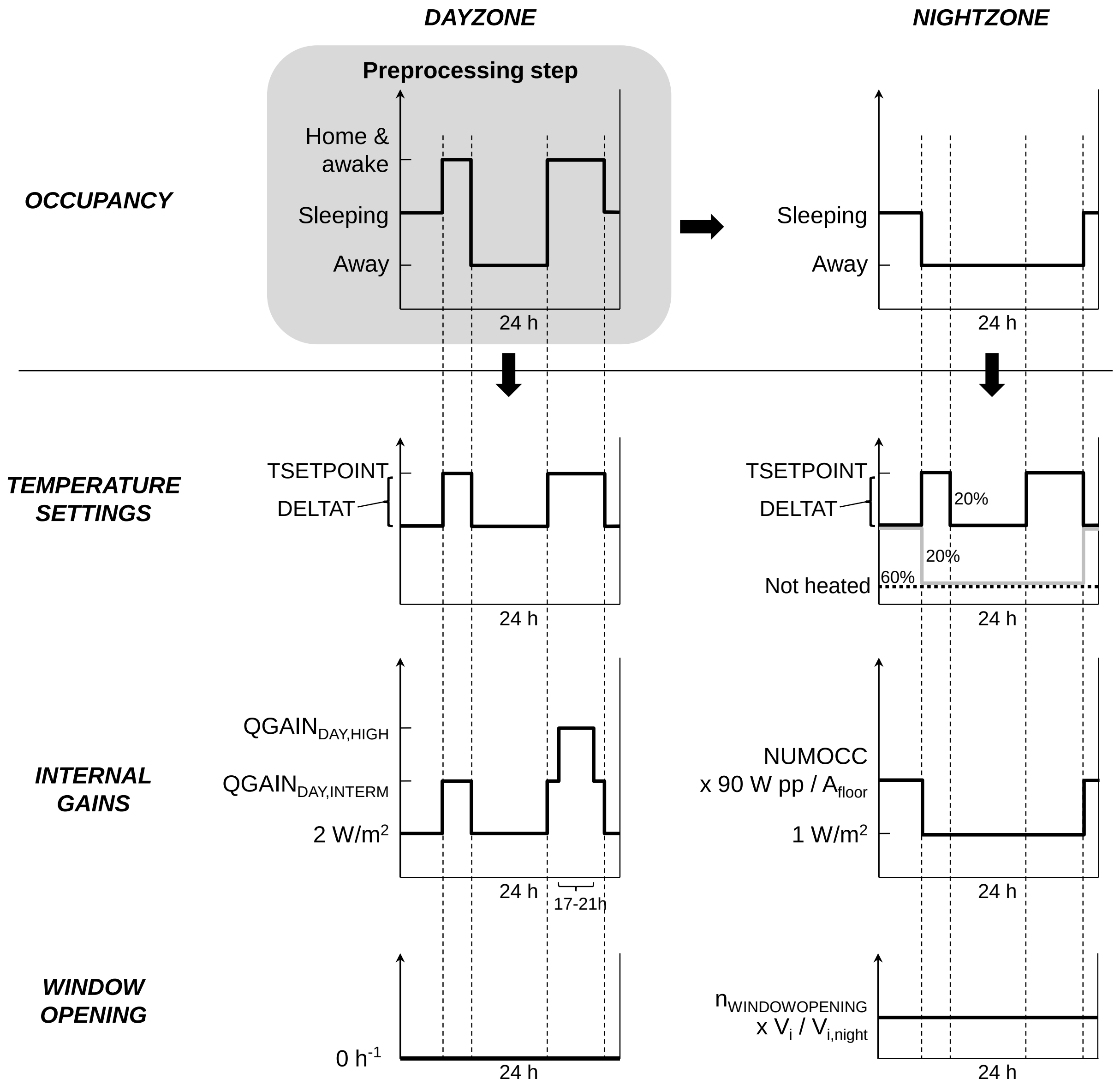


Figure 3.20: Schematic representation of final probabilistic behavioural model.

profiles (both week and weekend profile) as a preprocessing step. These profiles are directly imposed to (the virtual room thermostat of) the dayzone and as such define the sleeping hours in the nightzone. Based on the sampled heating preference parameters, the temperature settings in both day- and nightzone can be assigned. The same applies for the internal heat gains, where, if the household is present from 17 h to 21 h, a high level of heat gains is defined in the dayzone. The window opening is implemented as a constant air infiltration rate in the nightzone only, following Equation 3.5.

It must be noted that the behavioural model generates user behaviour profiles that are kept unaltered throughout the whole year: temporary lower occupancy rates like holidays or daytrips, temporary (manual) variations to the thermostat settings, ... are not included.

Probabilistic input distributions

The second element is responsible for the probabilistic set-up of the model. It consists of the probability distributions for each of the input parameters, needed as input to the Monte-Carlo analysis. In total, 13 parameters need to be sampled. This is shown in Table 3.17.

As the household characteristics will be used to correlate them to the occupancy profile and temperature settings, they need to be sampled too. Since the empirical frequency distribution functions of these characteristics, as visible in Figure 3.16, are difficult to fit in an analytical probability distribution function, it is decided to not apply any fitting but to keep the original dataset. This means the sampling will be done directly from the empirical cumulative frequency distribution (*ecdf*). The same applies to the sampling of the occupancy profiles (see Table 3.1). The setpoint temperature and the amount of setback are sampled following their fitted distributions as these proved to fit well with the dataset. When setback is applied (WHENSETBACK), is also based on the *ecdf* of the ECS-dataset.

Table 3.17: Probabilistic input distributions for the parameters of the probabilistic behavioural model. (N(μ,σ) or LogN(μ,σ): (log)normal distribution with fitted mean μ and fitted standard deviation σ; U(a,b): uniform distribution between a and b; ecdf(dataset): empirical cumulative distribution function based on the dataset)

HOUSEHOLD	1	NUMOCC	~ *ecdf*(ECS)
	2	AGECAT	
	3	INCOME	
	4	ACTIVITY	
OCCUPANCY	5	$\mathrm{PROFILE}_{WEEK}$	~ *ecdf*(Aerts2014)
	6	$\mathrm{PROFILE}_{WEEKEND}$	~ *ecdf*(Aerts2014)
TEMPERATURE SETTINGS	7	TSETPOINT	~ *N*(20.74 ; 1.66)
	8	WHENSETBACK	~ *ecdf*(ECS)
	9	DELTAT	~ *LogN*(1.49 ; 0.46)
	10	PATTERNNIGHT	p(1)=0.2 ; p(2) = 0.2 ; p(3) = 0.6
INTERNAL GAINS	11	QGAIN_{HIGH}	~ *U*(14 ; 20) W/m^2
	12	$\mathrm{QGAIN}_{INTERMED}$	~ *U*(6 ; 10) W/m^2
WINDOW OPENING	13	$n_{WINDOWOPENING}$	~ *LogN*(-1.46 ; 0.84)

In the nightzone, 3 different patterns can be followed (PATTERNNIGHT), each with their own probability as depicted in Figure 3.20. The high and intermediate internal heat gain levels in the dayzone are picked from a uniform distribution.

Correlation matrix

The third and final element provides in the generation of a consistent behavioural profile by mutually linking several parameters through their partial correlation coefficients. These coefficients are collected in the final correlation matrix C, to be used to generate correlated random numbers (see 3.2.2). This final matrix C is shown in Table 3.18. All coefficients are based on the ECS-database (Table 3.16), except from the correlations with PROFILE_{WEEK} and $\text{PROFILE}_{WEEKEND}$ (based on data Dorien Aerts).

Table 3.18: Correlation coefficient matrix C as implemented in the probabilistic behavioural model. Italic: correlation coefficients deduced from data Aerts et al. (2014) - see 3.3.1. All other coefficients: deduced from ECS-database.

	NUMOCC	AGECAT	INCOME	ACTIVITY	PROFILE_{WEEK}	$\text{PROFILE}_{WEEKEND}$	TSETPOINT	WHENSETBACK	DELTAT	PATTERNNIGHT	$\text{QGAIN}_{DAY,HIGH}$	$\text{QGAIN}_{DAY,INTERMED}$	$n_{WINDOWOPENING}$
NUMOCC	1	-0.34	0.51	0.40	*0*	*0*	0	0	0	0	0	0	0
AGECAT		1	-0.25	-0.70	*0.42*	*0.20*	0.10	-0.11	0.08	0	0	0	0
INCOME			1	0.48	*-0.26*	*-0.09*	0	0.11	-0.10	0	0	0	0
ACTIVITY				1	*-0.54*	*-0.20*	-0.09	0.11	-0.08	0	0	0	0
PROFILE_{WEEK}					*1*	*0.25*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
$\text{PROFILE}_{WEEKEND}$						*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
TSETPOINT							1	0	0.43	0	0	0	0
WHENSETBACK								1	0	0	0	0	0
DELTAT									1	0	0	0	0
PATTERNNIGHT										1	0	0	0
$\text{QGAIN}_{DAY,HIGH}$											0	0	0
$\text{QGAIN}_{DAY,INTERMED}$												0	0
$n_{WINDOWOPENING}$													1

3.5.2 Evaluation

A brief evaluation of the behavioural model is possible by looking at some aggregated output values. To do so, a stochastic set of 10 000 users is generated.

Reproducibility of the correlation matrix

By decomposing the correlation matrix C through the Eigenvector decomposition, a set of uncorrelated random numbers is converted to a new set of random, but now correlated, numbers (section 3.2.2). The performance of this method is evaluated here.

By means of illustration, the input distributions and density scatterplots of TSETPOINT and DELTA are shown in Figure 3.21, both for the original ECS-data and the modelled data for 10 000 users in a non-space filling LHS scheme (once correlated and once uncorrelated). As expected, due to the analytical expression of both variables, the model output distributions are much more smooth than the original empirical distributions of the ECS data. Consequently, also the density scatterplot is more smooth than the original one. Overall though, it can be concluded that the general tendency of the original scatterplot is very well reproduced by the behavioural model when the correlations are included. If not, the distributions of both individual data are of course maintained, yet their mutual tendency is lost. The use of correlations thus proves to be an interesting feature of the behavioural model: two variables can be linked to each other in a probabilistic way, thereby keeping the individual probabilistic distributions intact and without the need for an explicit and deterministic formulation of one parameter as a function of the other.

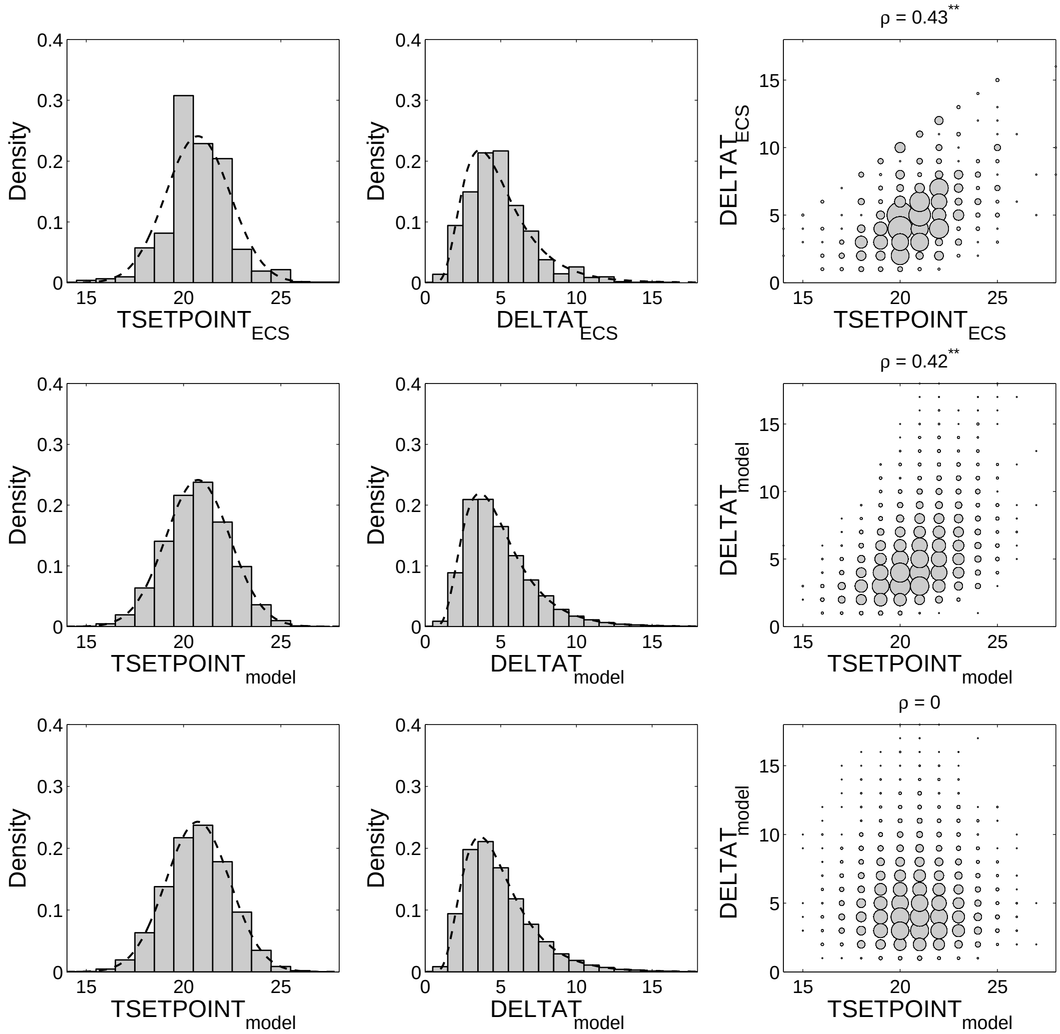
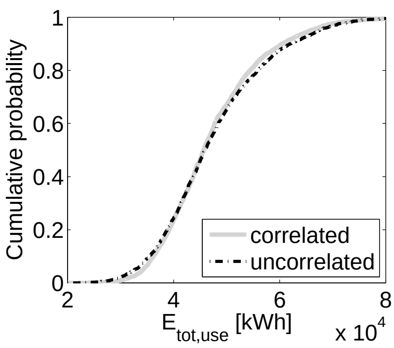


Figure 3.21: Comparison between the original ECS-data (top row) and the modelled data for 10 000 users (correlated: middle row ; unccorrelated: bottom row) for TSETPOINT, DELTAT and the combination of both (the sizes of the circles are proportional to the frequency of occurrence / the modelled data have been rounded to integers).
Dashed lines: normal (TSETPOINT) and lognormal (DELTAT) fit as used in the behavioural model.
*** : statistically significant at the α = 0.001 - level*

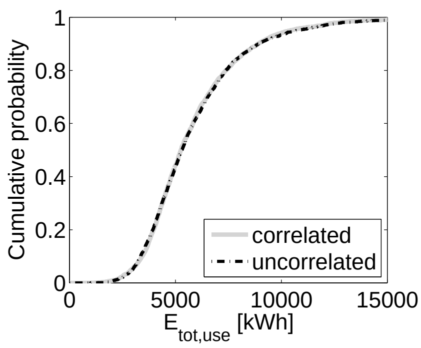
In Table 3.19 the correlation coefficients of all other parameters are shown, resulting from the above non-space filling LHS scheme for 10 000 users. The correlation coefficients of the original matrix C from Table 3.18 are all detected at the α = 0.001 level, yet slightly smaller than the implemented values. This means the implemented correlations are indeed reliably translated by the proposed method.

Throughout this dissertation however, the impact of user behaviour on a dwelling's energy use for space heating is calculated by running only 200 Monte-Carlo simulation runs per dwelling (see 5.2.2). When only 200 users are sampled following a space-filling LHS sampling scheme –see Table 3.20– only the highest coefficients are detected at the α = 0.001 level. When a less strict level of α = 0.01 is adopted, some extra correlations are visible (in bold), but still, the small original correlation coefficients (<0.20) remain undiscovered within the sample.

Consequently, and due to the coefficients of the current matrix C being rather small, the influence on the final energy use for space heating of using a correlated or uncorrelated behavioural model remains limited –see Figure 3.22. Only for a poorly insulated dwelling the spread of the correlated model is slightly smaller, indicating how the correlation matrix restricts the occurrence of extreme outliers. Nevertheless, the correlation matrix is maintained in the overall model for a more principal matter. If in the future other and higher correlations are found, the possibility is left open to insert these. For instance, when analysing a subgroup of the ECS-sample (see Chapter 6), significantly higher correlations are found between the heating preferences. Also, and although not done here, the correlation matrix can be extended with building characteristics in order to interconnect the household, user behaviour and building parameters.



(a) U_m = 1.24 W/(m^{2}K)



(b) U_m = 0.27 W/(m^{2}K)

Figure 3.22: Annual energy use for space heating under the probabilistic behavioural model (3000 users), for a poorly (a) and a well (b) insulated dwelling.

Table 3.19: Correlation coefficient matrix, based on 10 000 users, non-space filling LHS sampling scheme. (*) = p-value > 0.001

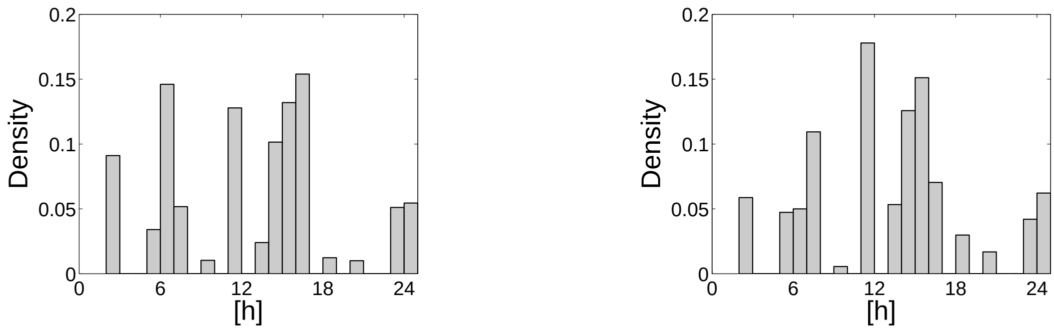
	NUMOCC	AGECAT	INCOME	ACTIVITY	$PROFILE_{WEEK}$	$PROFILE_{WEEKEND}$	TSETPOINT	WHENSETBACK	DELTAT	PATTERNNIGHT	$QGAIN_{DAY,HIGH}$	$QGAIN_{DAY,INTERMED}$	$n_{WINDOWOPENING}$
NUMOCC	1	-0.30	0.46	0.32	*	*	*	*	*	*	*	*	*
AGECAT		1	-0.20	-0.59	0.37	0.17	0.10	-0.11	0.09	*	*	*	*
INCOME			1	0.40	-0.24	-0.07	*	0.11	-0.08	*	*	*	*
ACTIVITY				1	-0.45	-0.16	-0.09	0.11	-0.08	*	*	*	*
$PROFILE_{WEEK}$					1	0.22	*	*	*	*	*	*	*
$PROFILE_{WEEKEND}$						1	*	*	*	*	*	*	*
TSETPOINT							1	*	0.41	*	*	*	*
WHENSETBACK								1	*	*	*	*	*
DELTAT									1	*	*	*	*
PATTERNNIGHT										1	*	*	*
$QGAIN_{DAY,HIGH}$											1	*	*
$QGAIN_{DAY,INTERMED}$												1	*
$n_{WINDOWOPENING}$													1

Table 3.20: Correlation coefficient matrix, based on 200 users, space-filling LHS scheme. (bold) = 0.001 < p-value ≤ 0.01 (*) = p-value > 0.01

	NUMOCC	AGECAT	INCOME	ACTIVITY	$PROFILE_{WEEK}$	$PROFILE_{WEEKEND}$	TSETPOINT	WHENSETBACK	DELTAT	PATTERNNIGHT	$QGAIN_{DAY,HIGH}$	$QGAIN_{DAY,INTERMED}$	$n_{WINDOWOPENING}$
NUMOCC	1	-0.27	0.45	0.28	*	*	*	*	*	*	*	*	*
AGECAT		1	*	-0.60	0.38	**0.18**	*	*	*	*	*	*	*
INCOME			1	0.40	**-0.22**	*	*	*	*	*	*	*	*
ACTIVITY				1	-0.52	*	*	*	*	*	*	*	*
$PROFILE_{WEEK}$					1	**0.19**	*	*	*	*	*	*	*
$PROFILE_{WEEKEND}$						1	*	*	*	*	*	*	*
TSETPOINT							1	*	0.39	*	*	*	*
WHENSETBACK								1	*	*	*	*	*
DELTAT									1	*	*	*	*
PATTERNNIGHT										1	*	*	*
$QGAIN_{DAY,HIGH}$											1	*	*
$QGAIN_{DAY,INTERMED}$												1	*
$n_{WINDOWOPENING}$													1

Daily heating duration

In the literature review concerning the heating preferences, values between 8-10 h (UK) / 11 h (NL) were estimated for the daily mean heating duration, based on both questionnaires and indirect measurements (Table 3.6 page 56). A similar aggregated outcome can be reproduced by the behavioural model. To do so, the total amount of hours is calculated in which the demand temperature is set to TSETPOINT in the dayzone. This amount of hours depends on the combination of the week and weekend profile with the moments when setback is applied, as reflected in Table 3.7. The outcome of the behavioural model for 10 000 users is given in Figure 3.23.



(a) weekday
μ_{sample} = 12.6 h ; σ_{sample} = 6.08 h

(b) weekendday
μ_{sample} = 13.1 h ; σ_{sample} = 5.63 h

Figure 3.23: Histogram of the daily amount of hours at TSETPOINT in the dayzone, as generated by the probabilistic behavioural model for 10 000 users.

When compared with the histograms of (estimated) daily heating duration as found in the literature (Figure 3.10 page 56), the simulated distribution is clearly less smooth. This is due to the deterministic definition of each of the 7 profiles, leading to a fixed amount of hours in each state for every profile. Some bundling is visible around the 6 - 16 - 24 h values, similarly as discovered in the literature histograms.

When comparing the summary statistics, the simulated results yield higher average heating hours than found in the literature: $\mu_{simulated}$ ~ 12-13 h against $\mu_{estimated}$ ~ 8-10 h (UK) / 11 h (NL). Of course, these values do not apply to the Belgian context, impeding a straightforward comparison. Nonetheless, a possible explanation for the low(er) heating durations is the rigorous linking of occupancy to the demand for space heating. The occupancy profiles of Table 3.1 show that most people go to sleep from 23h on and later. In the behavioural model, it is assumed that until then also the comfort temperature TSETPOINT is demanded for. This is not necessarily the case. In fact, the probability curve for the heating system being on, set up for English households by Huebner et al. (2013b) and shown in Figure 3.11, suggests that from 21h the majority of heating systems is already switched off (derived from continuously decreasing indoor temperatures).

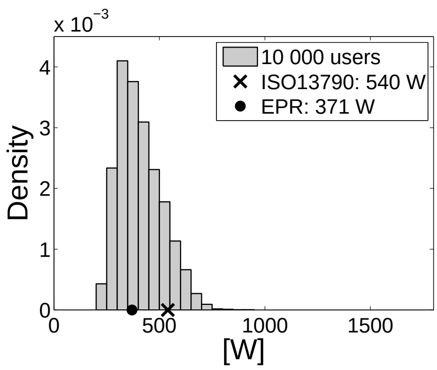
Level of internal heat gains

The implementation of the internal heat gains (occupants, lighting and appliances) is mainly based on the procedure as described in ISO/FDIS 13790 (2008): heat gains are expressed in W per m^2 floor area and vary depending of the type of rooms and the time of the day. This was slightly altered to better fit with the behavioural model: gains linked with the occupancy profiles, gains in nightzone depending on amount of occupants and introduction of stochastic gains.

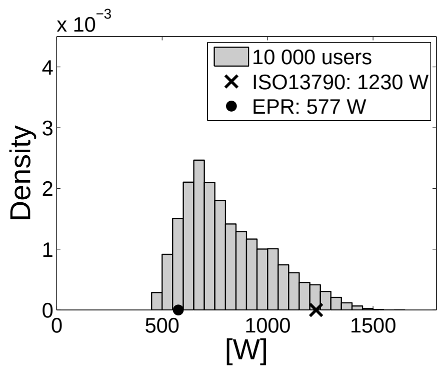
Unfortunately, no measurement data is available to check the reliability of the overall procedure. Instead, the implementation is compared with the deterministic values one would obtain when following the ISO/FDIS 13790 (2008) (see Table 3.12) or when following the implementation of internal heat gains in the Belgian energy performance calculation (EPR 2010). The latter expresses the internal heat gains as a constant value over time and only as a function of the internal volume of the dwelling V_i:

$$Q_{int,gain} = (0.67 + 220/V_i) \times V_i \qquad [\mathrm{W}] \tag{3.6}$$

The daily mean heat gains (week- and weekendday weighted averaged and summed for day- and nightzone) are shown in Figure 3.24. One can see how the outcome of the 3 methods can be quite different, certainly for the large dwelling. The EPR-value is situated more in the lower value range of the behavioural model, certainly for larger dwellings, while the opposite is true for the ISO13790 values.



(a) Small dwelling ($A_{floor,dayzone}$=50m^2, $A_{floor,nightzone}$=30m^2, V_i=224m^3)



(b) Large dwelling ($A_{floor,dayzone}$=108m^2, $A_{floor,nightzone}$=82m^2, V_i=517m^3)

Figure 3.24: Histogram of the daily mean internal heat gains, as generated by the probabilistic behavioural model for 10 000 users and compared with the deterministic values of ISO/FDIS 13790 (2007) and the Belgian energy performance calculation (EPR).

3.6 Overview and conclusions

Due to the importance of a correct user behaviour modelling in the energy performance gap and shortfall, this chapter is dedicated to the development of an evidence-based probabilistic behavioural model.

Occupancy profiles and their probabilities of occurrence are determined, based on the cluster analysis of Aerts et al. (2014) on a large-scale Belgian Time-Use Survey. These profiles prove to be strongly correlated to common household characteristics (age, income and activity level) and serve as input to the heating and internal heat gain time schedules.

The heating preferences are discussed in detail. Three main conclusions can be drawn. (i) The heating behaviour in the main living room(s) is quite well known. In the literature very similar set-point temperature distributions are found, suggesting that it is a rather invariant and well predictable thermostat setting. Useful probabilistic data is also found about the setback settings (when setback is applied and to which temperature). (ii) Empirical evidence is found that the heating time schedules (of the main living room(s)) are strongly linked to the times of presence of the inhabitants, justifying the overall working method of the behavioural model. (iii) In contrast with the main living rooms, almost no quantitative information is found on the extent of heating in the other rooms like bedrooms, hallways, ... The qualitative data available does affirm the basic principle of the behavioural model, namely that two thermal zones are considered within every dwelling: the dayzone (living rooms, kitchen, bathroom), heated to comfort temperatures, and the nightzone (bedrooms, hallway), rarely or never heated. To fill the missing gaps on the nightzone heating behaviour, pragmatic assumptions are made.

The ventilation behaviour of the inhabitants is considered only in terms of window opening behaviour. Due to time calculation constraints, air flows are not modelled in detail, so the convective heat losses associated with opening windows is assessed in a simplified, yet stochastic way. As the literature pointed out how mainly the bedrooms are vented, these convective heat losses are only assigned to the nightzone.

By lack of data, the internal heat gains, dissipated by the occupants, lighting, appliances and cooking, are included in a simplified way. Based on the different states of the occupancy profile, different (stochastic) internal gain levels are assigned.

Both a literature review and an analysis on the Belgian Energy Consumption Survey are performed to detect drivers for the previously mentioned user behaviour actions. Household characteristics prove to be strongly correlated to each other, but only weakly to heating behaviour. Also, no statistically significant link could be identified between the heating behaviour in the main living room and any building characteristic. However, a strong indication was found that the heating behaviour in the other rooms of the dwelling is influenced by both household and building characteristic, but unfortunately, no quantitative figures could be deduced.

Nevertheless, a relevant correlation matrix could be set up, providing correlations between household characteristics and occupancy levels, and household characteristics and heating behaviour in the main living room.

The so developed probabilistic behavioural model offers many opportunities. Firstly, as it is based on Belgian data sources whenever possible, it is believed to render user profiles that are representative for Belgian households. Secondly, due to the explicit modelling of intermittent and zonal heating, the physical part of the temperature takeback (discussed in section 2.4.1) is automatically accounted for. Thirdly, the possibility of including correlations is believed to be a major feature of this model. Not only because different parameters can be mutually linked, but also because this linking is done stochastically. Hence, the probabilistic nature of each of the parameters involved, and by extension the probabilistic nature of the overall behavioural model, remain intact.

Of course, some considerations must be made. By lack of data, severe assumptions had to be made to fill in the heating behaviour in the less inhabited parts of the dwelling. This harms the overall reliability of the model, since these rooms can take up a significant share of a dwelling. Further data collection concerning that heating behaviour aspect is thus primordial. Also, it is shown that the rigorous linking of occupancy with heating demand periods might overestimate the actual heating hours. Finally, by lack of data, the window opening behaviour and internal heat gains are modelled in a rather simplified way.

4

Development of generic building model

As the inappropriate implementation of standard user behaviour is believed to largely contribute to the performance gap (see chapter 2), a large deal of effort has been put in the development of realistic heating behaviour, characterised by both intermittent and zonal heating and reflected in the probabilistic behavioural model of Chapter 3. However, in order for this behavioural model to be of use in any building energy simulation, the shift has to be made from the common (quasi)-static calculation tools to a transient simulation tool with a more refined building model. How this is done is described within this chapter.

4.1 Methodology

The (quasi)-static calculation methods are not suitable for implementation of the probabilistic behavioural model. In these methods the intermittent heating cannot be incorporated directly (zonal heating can be accounted for by using a two-zone building model). Instead, any intermittent heating schedule needs to be converted to an equivalent indoor temperature, based on a certain heating schedule, global building characteristics like the building time constant and the heat transfer coefficient, and most often the calculation of a gain utilization factor (see SAP (2009), NEN7120 (2011), ISO/FDIS 13790 (2007)). The latter is a major drawback of the quasi-static methods. Based on a review of studies comparing dynamic methods with the monthly quasi-static ISO 13790 method, Kim et al. (2013) concluded that "*the utilization factors must be rigorously calibrated for the ISO 13790 approach to be more accurate*". This need for calibration of course strongly impedes a general working method and is not desired for in a probabilistic framework where many different user behaviour profiles are to be imposed in many different dwellings. Similarly, many other studies found significant discrepancies between static and dynamic methods and indicated the gain utilization factor in the quasi-steady state methods as predominant factor for these discrepancies (Loga et al. 1999, van Dijk et al. 2005, Wauman et al. 2013). Finally, Corrado and Fabrizio (2006, 2007) and Jokisalo and Kurnitski (2007) reveal the dependency of the gain utilization factor to the specific use and typology of the building.

Therefore, and despite a larger calculation time per dwelling, it is chosen to abandon the path of quasi-steady state calculations and adopt the transient simulation environment `TRNSYS 17` (to allow for the intermittent heating) in which a multi-zone building is modelled (to allow for the zonal heating).

It must be kept in mind that the final building model is meant to fit in a bottom-up modelling framework. Therefore the building model must be easily adaptable, require only a limited amount of input detail, be sufficiently fast in calculation time and generate, at the same time, a reasonably reliable and representative output. Reconciling these requirements with typical transient simulation modelling is obviously a difficult yet not impossible task. Throughout this chapter and where justified, simplifications and decisions are made to keep the overall building model manageable, yet still capable of producing a reliable output at heating season basis. The most important ones are listed here:

- Supported by the empirical evidence of chapter 3 *every dwelling is divided in only two zones*: a frequently heated dayzone and a less frequently heated nightzone. A further division in additional zones would seriously increase the calculation time and does not necessarily lead to higher accuracy due to the lack of data about the user behaviour in these additional zones.
- *No space heating system is modelled*, because it needs a considerable amount of input data (often unavailable at a larger scale) and strongly slows down the calculation. Instead, the transient simulation environment `TRNSYS` is only used to calculate the net energy demand, while space heating system efficiencies, derived from other studies, are used to convert this net energy demand to an energy use.
- *Ventilation and infiltration air flows are not modelled in detail*, again to reduce calculation time. Instead, they are assessed in a more simplified way.

Hence, on a 2.53 GHz Intel(R) Core(TM)2 Duo processor the final computation time for a single heating season totals 30 seconds per dwelling and per implemented user profile. When using the Monte-Carlo analysis to generate a reliable output distribution, typically 200 different user profiles and thus 200 simulations are required (see 4.6), leading to a total computation time of 100 minutes per dwelling.

To enhance and facilitate the implementation process, `MATLAB R2013a` (MATLAB 2013) is used as the central programming environment from which all adaptations in the `TRNSYS`-files are done automatically. This means that all pre- and postprocessing steps are managed for by `MATLAB` and that the `TRNSYS`-simulations are 'called' from within the `MATLAB`-environment whenever necessary.

Outline of the chapter

First, the building energy simulation tool TRNSYS, used in this work, is briefly elucidated (4.2). Afterwards, it is described how a generic implementation of the building model is made possible (4.3), followed by how the convective heat losses (4.4) and space heating system efficiencies (4.5) are modelled. Finally, the case study dwellings that will be used throughout this work is described (4.6).

4.2 Modelling tool: TRNSYS 17

TRNSYS 17 is a TRansient SYStems simulation program (TRNSYS 17 2010), used in a wide domain of applications (solar systems, low energy buildings and HVAC-systems[1], renewable energy systems, cogeneration). Its main feature is the modular structure, allowing to include individual components (either from the library either self-defined), send outputs of one component at inputs of another component and compose as such a global system.

In this dissertation TRNSYS is used as a building energy simulation tool, calculating a building's heating season net energy demand for space heating for a given outdoor climate and dwelling use. Since the net energy demand is externally converted to an energy use by using space heating system efficiencies (see further 4.5), no space heating system is modelled in TRNSYS. Hence, the multi-zone building model (called '*Type 56*') is the main component. As input data it needs the outdoor weather conditions, the building characteristics (orientation, geometry, building components) and the indoor boundary conditions, determined by the dwelling use. The latter is generated by the probabilistic behavioural model of Chapter 3 and transferred into the TRNSYS-environment.

The multi-zone thermal building model *Type 56* considers each zone as one single air node for which a convective heat balance is set up - see Figure 4.1:

$$C_{zone}\frac{dT_{air,zone}}{dt} = Q_{demand} + Q_{surf} + Q_{inf} + Q_{vent} + Q_{g,c} + Q_{cplg} \qquad [\mathrm{W}] \tag{4.1}$$

with C_{zone} and $T_{air,zone}$ respectively the internal heat capacity and air temperature of the zone, Q_{demand} the net heating or cooling demand, Q_{surf} the convective gains from the surfaces bordering the zone, Q_{inf} the infiltration losses, Q_{vent} the ventilation losses, $Q_{g,c}$ the internal convective heat gains (people, equipment, etc.) and Q_{cplg} the convective gains through coupled air flows with other zones.

C_{zone} is set to 10 times the heat capacity of the internal air volume, to account for both the air capacity and the additional capacity of furniture. Q_{inf} and Q_{vent} will be discussed in section 4.4. The internal convective gains $Q_{g,c}$ are straightforwardly defined as 50 % of the heat gains following from the probabilistic behavioural model (the other 50 % is emitted as internal radiative gains). Because no interzonal flows are considered, Q_{cplg} equals zero.

In order to calculate Q_{surf} additional heat balances are required for the inner and outer surface

[1] Heat, Ventilation and Air Conditioning

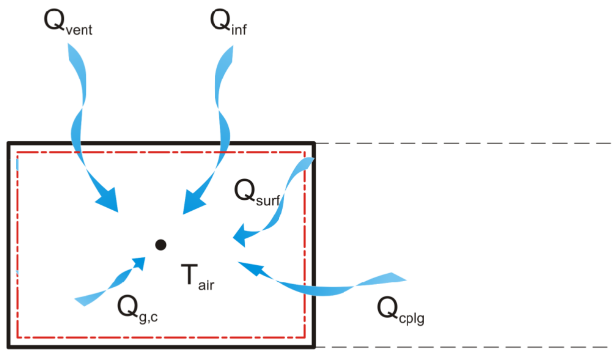


Figure 4.1: Convective heat balance for the zone air node. Source: TRNSYS 17 (2010)

temperatures of every wall and window bordering the zone. The conductive heat transfer between both surfaces is modelled according to the transfer function relations of Mitalas and Arseneault (1972). The outer surfaces are subject to convective heat transfer with the outside air (modelled by means of a convective heat transfer coefficient), shortwave solar radiation and longwave radiation exchange with the sky and the ground (modelled by means of view factors). The incoming solar radiation (both beam and diffuse and transmitted via external windows) is distributed over each of the inner surfaces according to absorptance weighted area ratios, while the internal radiative heat gains (people, equipment etc.) are distributed according to simple area ratios. The longwave radiation exchange between all inner surfaces and the convective heat gains Q_{surf} from these surfaces to the airnode are approximated by using the star network model of Seem (1987). More detailed internal and external radiation modes are available in `TRNSYS 17`, requiring three-dimensional input data and shader surfaces. As these modes strongly increase input effort and calculation time but only have a limited impact on the results in case of normal surface emissivities and normal glazing areas (manual TRNSYS 17 (2010)), they are not adopted here.

Every time step, the air node balance of every zone and all inner and outer surface temperature balances of the bordering walls and windows are solved through an iterative approach.

The outdoor weather conditions are implemented by using the METEONORM[2] datafile for Ukkel, Belgium. All simulations start at the 1st of August, allowing for the thermal mass to adapt to the outdoor conditions before the actual heating season starts, and end at the 30th of April. As no space heating system is modelled, the main dynamics are determined by the building responding to changing outdoor and indoor conditions, so the time step can be set rather large. A time step of 30 minutes is adopted, leading to a total computation time of 30 seconds per dwelling on a 2.53 GHz Intel(R) Core(TM)2 Duo processor.

[2] METEONORM files published by METEOTEST - see *www.meteotest.com*

4.3 Building envelope

This section describes the main input data required for the multi-zone TRNSYS building model: the orientation and geometry of the dwelling, the composition of the walls and windows and the air permeability of the building envelope. All these are available from the preprocessing steps in MATLAB and are stored in the following arrays TURN, GEOMETRY, WALL, INS and WIN. Any set of these 6 arrays univocally determines the geometric and thermal characteristics of the dwelling's building envelope. Each of the arrays is briefly discussed hereunder.

4.3.1 Generic orientation and geometry

To obtain a generic building model, the orientations are not chosen beforehand but are expressed relatively to the position towards the street. The turning angle TURN is set to 0° when the front facade is facing south and is positive in clockwise direction (see Figure 4.2-left). A visualisation of the generic building model is given in Figure 4.2-right and the corresponding generic input matrix GEOMETRY is given in Table 4.1 (middle column). By omitting building elements in the generic matrix, different typologies and configurations can be built, of which two examples are shown in Figure 4.3.

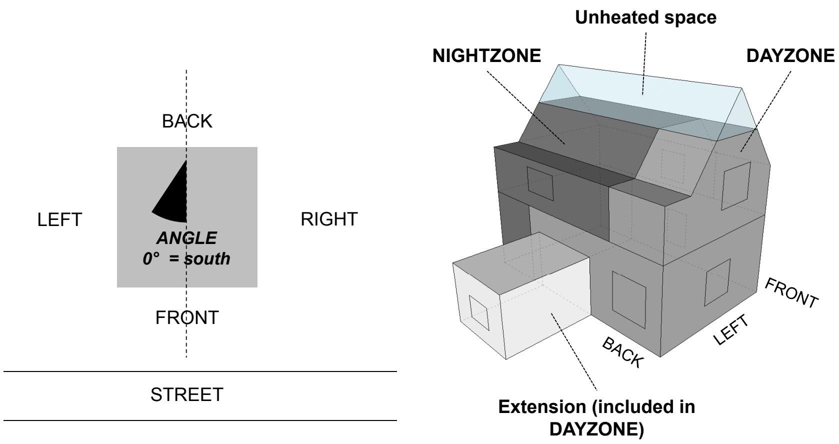


Figure 4.2: Generic building orientation and geometry.

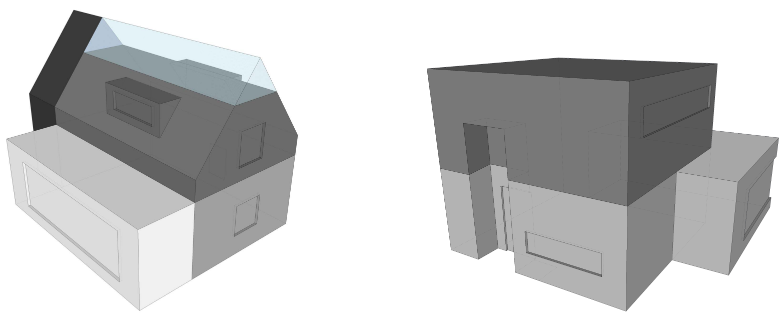


Figure 4.3: Examples of possible dwelling typologies and configurations (light grey: dayzone ; white: dayzone extension ; dark grey : nightzone ; black: adjacent dwelling).

Table 4.1: Input matrix GEOMETRY for generic building model (middle column) and input example for the semi-detached dwelling (right column) of Figure 4.3.

input matrix GEOMETRY					
		GENERIC		*EXAMPLE*	
		DAY	*NIGHT*	*DAY*	*NIGHT*
Volume	[m^3]	x	x	315.0	194.4
AWallFront	[m^2]	x	x	15.4	3.0
AWallLeft	[m^2]	x	x	25.3	17.0
AWallBack	[m^2]	x	x	0	6.8
AWallRight	[m^2]	x	x	0	0
AWinFront	[m^2]	x	x	10.8	2.3
AWinLeft	[m^2]	x	x	3.7	6.6
AWinBack	[m^2]	x	x	0	2.3
AWinRight	[m^2]	x	x	0	0
AFloorGround	[m^2]	x	x	82.3	0
AFloorBas	[m^2]	x	x	0	0
ARoofFlat	[m^2]	x	x	0	13.1
ARoofPitchFront	[m^2]	x	x	0	25.4
ARoofPitchBack	[m^2]	x	x	0	20.2
AWinRoofFlat	[m^2]	x	x	0	0
AWinRoofPitchFront	[m^2]	x	x	0	0
AWinRoofPitchBack	[m^2]	x	x	0	0
ACeilingUnheatedSpace	[m^2]	x	x	0	42.0
AWallLeftExt	[m^2]	x		8.37	
AWallBackExt	[m^2]	x		5.4	
AWallRightExt	[m^2]	x		8.37	
AFloorGroundExt	[m^2]	x		23.3	
ARoofFlatExt	[m^2]	x		23.3	
AWinExt	[m^2]	x		21.4	
AFloorIn	[m^2]	x	x	0	0
AWallIn	[m^2]	x	x	30	30
AFloorBetween	[m^2]	x		82.3	
AWallBetween	[m^2]	x		0	
PFloorGround	[m]	x	x	18.2	0
PFloorBas	[m]	x	x	0	0
PFloorGroundExt	[m]	x		14.0	

External dimensions are used as this is the main convention in Belgium. The generic building model consists of opaque walls in the 4 directions, one flat roof type and one pitched roof type, of which all can contain a certain window area, and also a slab-on-ground and a suspended floor. All elements are available for both zones. As many dwellings in Belgium have been extended in a later stage by adding an extra volume to the ground floor -often meant to enlarge the living space- this possibility is also built-in. For reasons of simplification the extension is limited to a rectangular volume at ground level, added to the dayzone, and can only have walls, with windows solely in the back facade, a slab-on-ground-floor and flat roof. Nevertheless, it allows for the implementation of building envelope elements that are different from and often better insulated than those of the original dwelling. Internal walls and floors are present too, as well as common walls and floor between both zones. It is assumed that no heat loss occurs via adjacent dwellings. This means that common walls with adjacent dwellings have to be implemented as internal walls: no heat loss is generated through these walls, while their thermal mass is still available to the indoor environment. Also, perimeter lengths (P) have to be provided to calculate the heat transfer via the ground (see further 4.3.3).

For both day- and nightzone, the possibility for an indoor ceiling to border an unheated space ('CeilingUnheatedSpace'; e.g. towards an inhabited attic) is included. This unheated space is not modelled as a separate zone, but is modelled as a boundary temperature at the outer surface of the ceiling element. Within every time-step this temperature is calculated from the unheated space heat balance, taking into account the ventilation and transmission losses to out- and indoor environment (solar and internal gains and heat storage in the walls bordering the unheated space are not considered).

Note that the generic geometry is not absolute and cannot cover all possible dwelling typologies. Yet, as it is meant to fit in the broader scope of a bottom-up model at city, district or national level, the amount of detailing and differentiation is assumed sufficient for that aim. For that same reason, no shading objects like window overhangs or surrounding buildings are modelled.

In contrast, the inputs of the `GEOMETRY`-array are to be done in terms of surface areas, and not in terms of width of the dwelling, height, length etc. The latter allows for an even more straightforward implementation of dwellings (dwellings can be conceived as simple rectangular volumes −see for example Hens et al. (2001)), yet at the expense of geometric detailing and similarity with actual existing dwellings. When working at national building stock scale, these strongly simplified geometries might prove worthwhile. However, when working at a smaller scale like district or city level, dwelling geometries that correspond more to actual, typical dwellings are preferred. Therefore the latter option is retained in the generic building model developed in this dissertation. If desired though, a preprocessing step could be developed in which such simple geometries are translated into areas, subdivided into the required orientation and building elements, and transferred into the `GEOMETRY`-array.

4.3.2 Building envelope elements

Each of the wall, floor, roof and window components of Table 4.1 is assigned one single composition. A library of opaque and transparent building envelope elements is made, containing the possible and desired compositions. The specific compositions for each of the opaque elements are picked from the library, stored in the `WALL` matrix and then combined with a corresponding insulation thickness (in [m]), stored in the `INS` matrix - see Table 4.2. The window composition (combination of glazing type and frame) is stored in the `WIN` matrix - see Table 4.3. Note that the whole dwelling is supposed to have the same window type 'Window', except for the extension of the dayzone which can have a different type 'WindowExt'. The combination of `WALL`, `INS` and `WIN` forms the univocal declaration of the building envelope elements of the total dwelling.

Thermal bridges are not accounted for in the current generic building model.

Table 4.2: An example of the input matrices `WALL` and `INS`, which together define the characteristics of the opaque elements of the building model.

	WALL	INS
Wall	WALL.CAV.BRICK.AIR.BRICK	0
FloorGround	FLOORSLAB.CONCRETE.PUR.SCREED.TILES	0
FloorBas	FLOORSUSP.CONCRETE.PUR.SCREED.TILES	0
RoofFlat	ROOF.LIGHT.WOOD.PUR	0.05
RoofPitch	ROOF.LIGHT.WOOD.MW	0.06
CeilingUnhS	CEILINGUNHS.WOOD.MW	0.06
WallExt	WALL.CAV.BRICK.PUR.BRICK	0.08
FloorGroundExt	FLOORSLAB.CONCRETE.PUR.SCREED.TILES	0.05
RoofFlatExt	ROOF.LIGHT.WOOD.PUR	0.15
FloorIn	FLOORIN.MASS.CONCRETE	– [a]
WallIn	WALLIN.MASS.BRICK	– [a]
FloorBetween	FLOORBETWEEN.MASS.CONCRETE	– [a]
WallBetween	WALLIN.MASS.BRICK	– [a]

[a] Interior building elements are not assigned an adaptable insulation thickness. If an insulation layer is present in the interior element, the thickness is fixed in the wall definition itself.

Table 4.3: An example of the window matrix `WIN`, which defines the characteristics of the transparent elements of the building model. E.g. ' SINGLE568.G855.WOOD*' = single glazing with U-value of 5.68 W/(m^{2}K) and g-value of 0.855 [-] in a wooden frame.*

	WIN
Window	SINGLE568.G855.WOOD
WindowExt	DOUBLE143.G605.WOOD

4.3.3 Heat transfer via the ground

Both for slab-on-ground floors and floors above (unheated) basements, the ground heat losses are calculated following the international standard NBN EN ISO 13370 (2008). To implement these monthly ground losses into the transient `TRNSYS`-environment, the following procedure is followed:

- **slab-on-ground floor**
  For this type of floor, the Annex D: "*Application to dynamic simulation programs*" of NBN EN ISO 13370 (2008) is followed. The average component of the heat transfer via the ground is represented by the calculated heat flow $Q_{m,ground,13370}$ and is implemented as a negative convective heat gain (=extraction of convective heat from the zonal node). To account for the dynamic and buffering effect of the (heavy) floor and the ground underneath, the floor is also modelled as a single element consisting of each layer in the floor construction plus 0.8 m depth of ground[3] and an adiabatic boundary condition at the outer side of it. As such, no net heat transfer will occur through this element at the long-term, but the accessible thermal mass of it allows for including a damping effect on the indoor environment.
- **suspended floor above (unheated) basement**
  The NBN EN ISO 13370 (2008) does not give guidelines for implementation of these types of floors into dynamic simulation programs, so our own method is followed here. The floor is

[3] The standard NBN EN ISO 13370 (2008) prescribes a 1 m depth of ground. Due to the stability criteria in `TRNSYS` only 0.8 m can be modelled.

modelled as a single element consisting of each layer in the floor construction with a boundary temperature on the outer surface of it. This monthly varying boundary temperature $T_{m,basement}$ is determined in such a way that the total heat flow through the floor element will equal the monthly heat flow $Q_{m,13370}$:

$$T_{m,basement} = T_{m,i} - \frac{Q_{m,susp,13370}}{A_{floor}}(R_{si,down} + R_{floor}) \qquad [^{\circ}\mathrm{C}] \tag{4.2}$$

with $T_{m,i}$ the monthly mean indoor temperature[4], A_{floor} the total area [m^2] of the floor above basement, $R_{si,down}$ = 0.17 m^{2}K/W the interior surface coefficient (both convection and radiation), R_{floor} the thermal resistance of the floor element [m^{2}K/W].

4.4 Model convective heat losses

In reality, the in-situ air change rate of a dwelling is the resultant of 3 possible phenomena:

- infiltration through the building envelope
- hygienic ventilation (if a ventilation system is present)
- window opening

To allow for an accurate assessment of the interactions of all of these phenomena, a detailed airflow model should be developed, including different zones at each storey and facade of the dwelling, connected to other internal zones and the external environment by air flow paths, representing the ventilation system components and air leakage paths (Janssens et al. 2009). However, since the building model is to fit in a wider bottom-up scale and the calculation time should remain limited, this working method is unfeasible in practice and a more simplified approach is needed.

In this work, the procedure of the international standard ISO/FDIS 13790 (2008) is followed, in which the different air change rates (in/-exfiltration through building envelope, hygienic ventilation through the ventilation system and ventilation through window opening) are calculated separately and superposed to form the total air flow. As discussed in the behavioural model (section 3.3.7), the window opening behaviour is incorporated as a stochastic ventilation rate in the nightzone. So, only infiltration and hygienic ventilation are assessed in this section.

Note that no interzonal air flows are taken into account. In reality, internal doors are often opened and closed, allowing for internal air to move from one room/level to another and leading to convective heat transfer within the dwelling. Yet, practically no information is available on when internal doors are open/closed. Also, the so induced air movements are strongly influenced by the other air flows through infiltration and ventilation systems, so again, all phenomena should be modelled simultaneously which is unfeasible in practice. By neglecting the interzonal air flows, only conductive heat

[4]see Annex A.2: "*Calculation of ground heat flow rate*" of NBN EN ISO 13370 (2008) for which the following values are assumed here: $T_{i,average} = 21^{\circ}C$, $T_{i,amplitude} = 3^{\circ}C$ and $\tau = 1$.

transfer is considered between day- and nightzone, possible leading to an underestimation of actual heat transfer and, for example, to too low nightzone temperatures. This should be kept in mind when interpreting the final results.

4.4.1 Infiltration

The airtightness of the building envelope is typically measured by a fan pressurization test, from which the air flow $\dot{V}$ [m^3/h] is characterized by a power-law relationship with the air pressure difference between in- and outdoor environment ΔP [Pa]:

$$\dot{V}(\Delta P) = C \cdot \Delta P^n \qquad [\mathrm{m^3/h}] \tag{4.3}$$

with C the air leakage coefficient [m^3/(h Pa^n)] and n the air flow exponent [-]. In residential dwellings, this air flow exponent typically equals 0.6 (Hens 2010c). The air permeability of the dwelling is then given by the characteristic n_{50}-value, being the amount of air changes per hour under a pressure difference of 50 Pa between in- and outdoor environment:

$$n_{50} = \frac{\dot{V}(\Delta P = 50\ \mathrm{Pa})}{V_i} = \frac{C \cdot 50^n}{V_i} \qquad [1/\mathrm{h}] \tag{4.4}$$

with V_i the dwelling volume [m^3].

Under normal meteorological conditions the air pressure differences over the dwelling will be much lower than 50 Pa. As such, the measured air change rate n_{50} needs to be converted to a realistic, in-situ air change rate n_{inf}. To do so, different methods exist, from very simplified single-zone models like the Lawrence Berkeley National Laboratory (LBNL) Infiltration model (Sherman 1987), to complex multi-zone models like `CONTAM` (Dols and Walton 2002) and `COMIS` (Feustel and Rayner-Hooson 1990). For the latter models the amount of necessary input data is large and detailed, information that is often unavailable on an aggregated scale.

Therefore, it is chosen to opt for the simplified LBNL Infiltration model. In this model, the infiltrated air flow $\dot{V}_{inf}$ [m^3/h] is calculated by multiplying the effective leakage area ELA [m^2] by the specific infiltration s [m/s]:

$$\dot{V}_{inf} = ELA \times s \qquad [\mathrm{m^3/h}] \qquad \text{with} \qquad \begin{cases} ELA = \frac{\dot{V}(\Delta P = \Delta P_r)/3600}{\sqrt{2\Delta P_r/\rho_a}} & [\mathrm{m^2}] \\ s = 3600 \cdot \sqrt{f_w^2 v^2 + f_s^2 |\Delta T|} & [\mathrm{m/h}] \end{cases} \tag{4.5}$$

with ΔP_r the reference pressure difference [Pa], typically taken equal to 4 Pa, ρ_a = 1.2 kg/m^3 the density of air, f_w the infiltration wind parameter [-], v the wind speed [m/s], f_s the infiltration stack parameter [m/(sK$^{1/2}$] and $\Delta T = T_{i,a} - T_{e,a}$ the indoor-outdoor air temperature difference [°C]. The term $\dot{V}(\Delta P = \Delta P_r)$ is evaluated via Equation 4.3, with C=$n_{50}\,V_i/50^n$ (Equation 4.4). Following Sherman (1987), typical single-family houses values for the wind and stack parameters are $f_w = 0.13$ and $f_s = 0.12$ [m/(sK$^{1/2}$]. The wind speed v and outdoor air temperature $T_{e,a}$ are available for every time-step from the METEONORM-file. The dwelling air temperature $T_{i,a}$ is defined as the zone volume weighted mean of both zone air temperatures and is also available for every time-step via the TRNSYS building model:

$$T_{i,a} = \frac{\Sigma(V_{i,j} \cdot T_{i,a,j})}{\Sigma V_{i,j}} \qquad [^\circ\mathrm{C}] \tag{4.6}$$

with $V_{i,j}$ and $T_{i,a,j}$ the volume [m^3] and air temperature [°C] of zone j respectively. When dividing the infiltrated air flow $\dot{V}_{inf}$ through the dwelling's volume V_i, the infiltration air change rate n_{inf} is obtained, being the amount of air changes of the total dwelling per hour:

$$n_{inf} = \frac{\dot{V}_{inf}}{V_i} \qquad [\mathrm{h}^{-1}] \tag{4.7}$$

When calculating these air change rates for the freestanding dwelling of section 4.6 the daily mean values of Figure 4.4 are obtained.

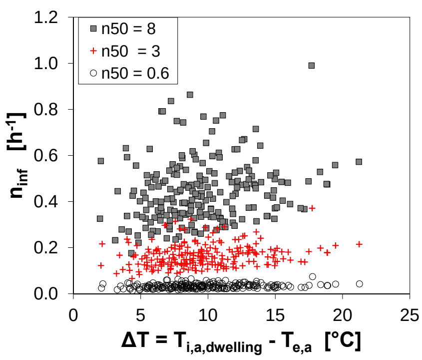


Figure 4.4: Daily mean infiltration air change rates [h^{-1}] as simulated following the LBNL infiltration model (Sherman 1987) on a freestanding dwelling (see case study in section 4.6).

The mean annual infiltration rates are n_{inf} = 0.44, 0.17 and 0.033 h^{-1} for the airtightness levels n_{50} = 8, 3 and 0.6 h^{-1} respectively, corresponding to a mean scaling value n_{inf}/n_{50} of 0.055 - 0.056 for all airtightness levels. This scaling value 0.056 is in close accordance to the findings of Janssens et al. (2006). In this study, an in-depth Monte-Carlo analysis is performed on a freestanding dwelling where the air flow rates through the building envelope air leakages and the ventilation system were deduced based on a detailed multi-zone model in COMIS (Feustel and Rayner-Hooson 1990). When analysing the air infiltration rates separately, a median scaling value of 0.055 was found, with an average value of 0.061. This gives good confidence that the simplified LBNL-model, used in this work, can serve as a fast, but reliable alternative for the more complex models.

Implementation in the building model

Because of the building model consisting of 2 zones, the total calculated air flow $\dot{V}_{inf}$ needs to be distributed over both zones. In reality, all depends on the characteristics of both zones and on how they are mutually connected: amount and location of air leakages, the degree of wind shielding conditions, the presence of more or less partition walls with constraining transfer openings between windward and leeward facade (Janssens et al. 2009), the presence of an open hallway connecting both zones, whether internal doors are frequently opened, etc. It is evident that in practice, this degree of complexity cannot be translated within a generic building model that is to be used in a large-scale bottom-up framework. Therefore, a more simplified approach is adopted. Because in- and exfiltration to a great extent occur proportional to the area in contact with outside (the more a room has outer surfaces, the more in- and exfiltration can occur) the air infiltration flow $\dot{V}_{inf}$ is distributed over both zones by their heat loss area ratio, leading to an air infiltration flow $\dot{V}_{inf,j}$ for zone j:

$$\dot{V}_{inf,j} = \dot{V}_{inf} \cdot \frac{A_j}{\Sigma A_j} \qquad [\mathrm{m^3/h}] \tag{4.8}$$

with A_j [m^2] and ΣA_j [m^2] the heat loss area of zone j and the total dwelling respectively. The convective heat losses $Q_{inf,j}$ for zone j then equal:

$$Q_{inf,j} = \rho_a \cdot c_a \cdot \frac{\dot{V}_{inf,j}}{3600} \cdot (T_{i,a,j} - T_{e,a}) \qquad [\mathrm{W}] \tag{4.9}$$

with ρ_a [kg/m^3] and c_a [J/(kg K)] respectively the density and heat capacity of air, $T_{i,a,j}$ [°C] the indoor air temperature of zone j and $T_{e,a}$ [°C] the outdoor air temperature.

4.4.2 Hygienic ventilation

Here the so-called 'hygienic' air flows are considered which are caused by intentional ventilation of the dwelling and which are meant to guarantee a good indoor air quality. To do so, different ventilation systems exists (NBN D 50-001 1991):

- No system: no grilles or vent openings - (peak) ventilation is only possible by opening windows and/or doors
- System A: natural supply and exhaust via grilles and vent openings
- System B: mechanical supply and natural exhaust (rarely used)
- System C: natural supply via grilles and vent openings, mechanical exhaust
- System D: balanced ventilation (both mechanical supply and exhaust), often combined with a heat recovery unit

When no ventilation system is installed, as is typically the case in old, unrenovated dwellings, these hygienic ventilation losses do not need to be modelled and it is sufficient to only calculate with the infiltration losses. In all other cases, an estimation of the air change rates due to the ventilation system should be made. To do so, two common methods exist.

Air change rates can be estimated by relying on the design guidelines. In Belgium, every ventilation system is to be designed according to the requirements of the Belgian residential ventilation standard (NBN D 50-001 1991). This standard imposes design air flows per m^2 floor area for the supply, transit and exhaust and this for different room functions. In case of system A and C, the vent openings must be designed such that the design flow rates for every room separately are delivered at 2 Pa pressure difference. For a fully balanced ventilation system D no individual component requirements are set, it is only required that the total system is able to deliver each of the design flow rates. Consequently, the standard offers information about the minimal requirements of the system, but not about the actual in-situ air change rates due to the installed systems. As it is our aim to come to a close prediction of actual energy use of a dwelling, it is important to know if discrepancies exist between design and actual flow rates and if so, how large they are.

In the '*Clean Air, Low Energy*' study of VITO et al. (2012b) the ventilation air flows have been measured in 25 recent Belgian dwellings, all equipped with a mechanical exhaust ventilation system (3 with system C, 22 with system D w/o heat recovery unit). Even when the ventilation systems were set to their maximum selectable flow rate, the actual air flow rates were significantly lower than the design values - see Figure 4.5. In normal conditions (also measured) the situation is even worse, because the occupants operated their ventilation system at much lower flow rates than prescribed. Amongst others, noise and draft were the main reasons given by the occupants doing so. Additionally, most occupants did not perceive ventilation as necessary (VITO et al. 2012b). Similar behaviour of putting the ventilation unit to one of the lower positions is observed in other measurement campaigns (Janssens et al. 2006, van Holsteijn and Li 2014).

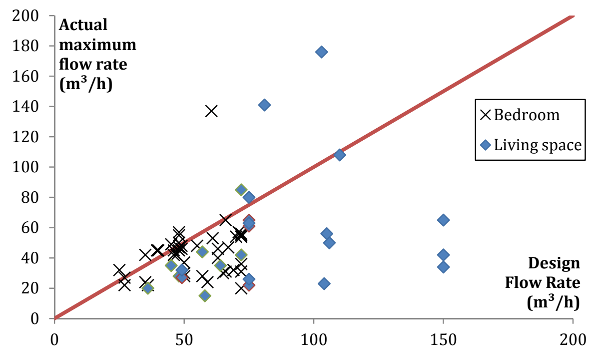


Figure 4.5: Actual maximum mechanical flow rates against design flow rates for living space and bedroom in 16 Belgian dwellings, equipped with system D with heat recovery unit. Source: VITO et al. (2012b)

In the study of Janssens et al. (2006) simulations were used to investigate to what extent design flow rates are delivered. To do so, a detailed multi-zone ventilation model was developed in `COMIS` (Feustel and Rayner-Hooson 1990) for different dwelling typologies. Ventilation systems A, C and D were implemented following the requirements of the NBN D 50-001 (1991). For the freestanding dwelling it was found that actual calculated supply rates were on average about 1.4 (system C) to 1.9 (system A) times smaller than the design supply rate. Only for system D the actual supply rate was very similar to the designed one. For other dwelling typologies, similar trends were found: for the same design flow rates, system D delivers the highest actual flow rates, almost equal to the designed ones, followed by system C and then system A. Yet for the conclusions about system D, it has to be kept in mind that the system D was assumed to work at nominal design power, while in reality occupants systematically put the ventilation unit to lower settings (see above). Nevertheless, it can be concluded that implementing ventilation rates solely based on the design values does not necessarily reflect actual ventilation rates reliably.

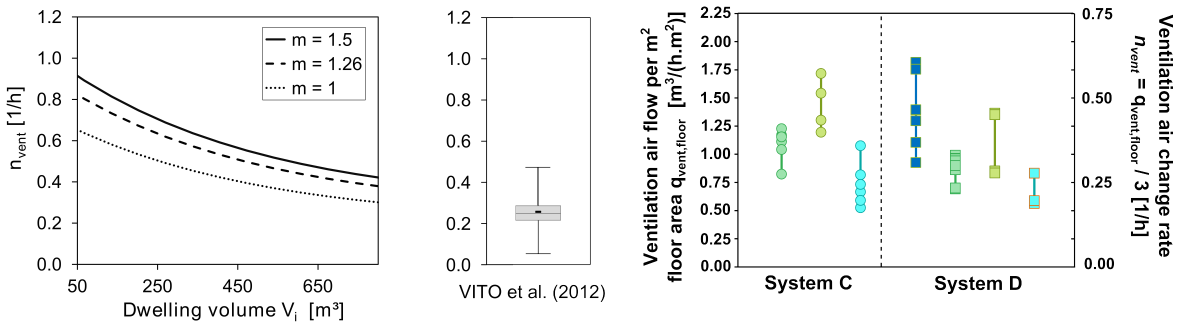
Apart from the design standards, ventilation rates are also estimated in the Belgian energy performance assessment regulation (EPR 2010) in order to calculate the heat losses through ventilation. Here, the air flow rate (both supply and exhaust) is predicted as:

$$\dot{V}_{vent} = m \cdot V_i \cdot (0.2 + 0.5\exp(-V_i/500)) \qquad [\mathrm{m}^3/\mathrm{h}] \tag{4.10}$$

with V_i the total dwelling volume [m^3] (based on exterior dimensions) and m a correction factor depending on the execution quality and characteristics of the system [-] (EPR 2010). By default, the m-factor is set to 1.5, independently of the ventilation system. If the system is demonstrated to perform better (for details see EPR (2010)), the m-factor can drop to a minimum of 1.26 for system A and to a minimum of 1 for system C and D. This implies that the ventilation air change rates n_{vent} = $\dot{V}_{vent}/V_i$ [h^{-1}] can vary within the limits as shown in Figure 4.6a.

By means of comparison a boxplot of measured ventilation air change rates is shown in Figure 4.6b, taken over from the previously mentioned study of VITO et al. (2012b) with the ventilation systems C and D now at their normal setting. Average air change rate is 0.25 h^{-1}, the median equals 0.24 h^{-1}. 50 % of all values lie within the interval [0.2 - 0.3] h^{-1} (grey box). It is clear how the method of the Belgian energy performance assessment systematically overestimates the actual air change rates.

In Figure 4.6c the results are shown from a recent measurement campaign in 62 Dutch dwellings (van Holsteijn and Li 2014). In this campaign many variants of the ventilation systems C and D have been monitored during one year (normal or self-regulating trickle vents, with or without heat recovery, with or without CO_2 and/or relative humidity sensors, etc.). The original results of van Holsteijn and Li (2014) are expressed in mean ventilation air flow per square meter floor area $q_{vent,floor}$



(a) Modelled following the Belgian energy performance assessment (EPR 2010): n_{vent} = $\dot{V}_{vent}/V_i$ with $\dot{V}_{vent}$ cfr. Equation 4.10

(b) Measurements in 25 Belgian dwellings. Source: VITO et al. (2012b)

(c) Measurements[a] in 62 Dutch dwellings. Source: van Holsteijn and Li (2014).

[a] A storey height of h=3m is assumed to estimate n_{vent} as $q_{vent,floor}/3$ (right Y-axis)

Figure 4.6: Ventilation air change rates n_{vent} [h^{-1}]: modelled (a) and measured under ventilation systems C and D (b and c).

[$m^3/(h.m^2)$], impeding a proper comparison. Therefore, and by lack of more detailed geometric data, an estimate of the ventilation air change rate n_{vent} is made by assuming a storey height h of 3 meter and by calculating n_{vent} as $q_{vent,floor}/h$. Again, though less prominent, the so estimated air change rates of systems C and D tend to be lower than those of Figure 4.6a. Interestingly also, despite the different variants measured, no substantial difference is observed in the ventilation rates for system C and D.

For system A it is more difficult to draw any conclusions because no measurements results are available. Yet, simulations (Janssens et al. (2006),Janssens et al. (2009)) show that system A leads to somewhat lower ventilation rates than mechanical exhaust ventilation systems (system C), suggesting that also for system A the actual air change rates are likely to be overestimated.

The above has pointed out how, despite being used frequently in building energy simulations, neither the imposed design guidelines nor the Belgian energy performance assessment guarantee a reliable estimation of actual ventilation air change rates. Therefore none of these procedures will be followed. Instead, and even though it is a more simplified approach than the previous procedures, it is chosen to directly rely on the measurements in the aforementioned '*Clean Air, Low Energy*' study (VITO et al. 2012b). Both for system C and D a ventilation air change rate of n_{vent} = 0.25 h^{-1} is adopted. When system A is implemented, the n_{vent}-values for system C and D are multiplied by 0.9, being the reduction factor of the system A's air flows found through the simulations of Janssens et al. (2006).

Implementation in the building model

The ventilation air change rate is imposed in every zone, leading to a hygienic ventilation flow $\dot{V}_{vent,j}$ for zone j:

$$\dot{V}_{vent,j} = n_{vent} \cdot V_{i,j} \qquad [m^3/h] \tag{4.11}$$

The convective heat losses through hygienic ventilation for zone j then equal:

$$Q_{vent,j} = \rho_a \cdot c_a \cdot \frac{\dot{V}_{vent,j}}{3600} \cdot (T_{i,a,j} - T_{supply,a}) \qquad [W] \tag{4.12}$$

with ρ_a [kg/m^3] and c_a [J/(kg K)] respectively the density and heat capacity of air, $T_{i,a,j}$ [°C] the air temperature of zone j and $T_{supply,a}$ [°C] the supply air temperature:

$$T_{supply,a} = T_{e,a} + \eta_{vent,heatRecovery} \cdot (T_{i,a} - T_{e,a}) \qquad [°C] \tag{4.13}$$

with $T_{i,a}$ the zone volume weighted dwelling air temperature, given in Equation 4.6, and $\eta_{vent,heatRecovery}$ the thermal efficiency of the heat recovery unit. If no heat recovery unit is present, this efficiency is set to 0. If a heat recovery unit is present, an efficiency of 0.7 is chosen, based on the values on heat recovery device efficiencies provided by CIBSE (2005).

4.5 Model heating system for space heating

A space heating system typically contains different subsystem levels: generation, storage, distribution, emission and control. The final efficiency of the heating system is not only bounded by the efficiencies of each of the subsystems and their mutual influences, but also by the complex interaction between these subsystems and both the dwelling and its occupants. An integrated approach should thus be followed, in which a dynamic building energy simulation is set up that includes both the building, inhabitants and heating system.

However, this working method is unfeasible in the framework of this research. The reason is twofold. At first, the detailed modelling of a heating system into the TRNSYS-environment heavily slows down the calculation time. This is undesired as both the later probabilistic and bottom-up approach require a large amount of individual building simulations. Secondly, many input parameters are needed to feed such a detailed simulation, information that is often unavailable at a larger scale. Although it is possible to make a variety of assumptions to fill in the unknown parameters, one might question the relevance of using such a detailed, inclusive approach on the one hand while many of the input parameters are highly uncertain on the other hand.

Therefore, a simplified, more widely used approach is followed: the calculation of the net energy demand $E_{net,demand}$ is done independently of the heating system, after which the total energy use $E_{tot,use}$ is obtained by applying an overall heating system efficiency coefficient $\eta_{overall,heat}$ [-]:

$$E_{tot,use} = \frac{E_{net,demand}}{\eta_{overall,heat}} \qquad [J] \tag{4.14}$$

In the following, the determination of the net energy demand $E_{net,demand}$ and the overall heating system efficiency $\eta_{overall,heat}$ are discussed.

4.5.1 Net energy demand

The net energy demand is obtained from the dynamic building simulation in TRNSYS. The building model *Type 56* has an in-built 'ideal heating' component, which is conceived as a massless, ideal heater, meaning no generation, distribution, emission or control losses are accounted for. The net energy demand is then the heat supplied by this ideal heating equipment to maintain the desired indoor temperature.

The available heating power can be either limited or not. In the latter case the desired air temperature is immediately reached the next time-step and kept perfectly stable throughout the entire heating period. Overheating is still possible, unless also the (ideal) cooling equipment is activated (not the case in this work). A radiative fraction of the heating power is to be defined in the range of [0-0.99], with 0 reflecting pure air heating, 0.3 and 0.5 reflecting convecto-radiators and floor heating respectively (Hens 2010a) and 0.99 being the maximum amount of radiative fraction to ensure a stable control of the heating equipment. The radiative fraction is supplied as an internal radiative gain and directly distributed to the walls and windows of the zone via area weighted ratios.

In section 3.3.3 it is described why in this dissertation it is chosen to *not* control the heating system on the operative temperature, defined as $T_{op,i}$ = 0.5 $T_{air,i}$ + 0.5 $T_{rad,i}$: (i) one cannot rely on the typical design ranges of operative temperature to represent actual indoor condition and (ii) large-scale information on actual operative temperatures in existing residential buildings is very scarce. Instead however, large-scale information is available on self-reported temperatures, which are most often the temperatures as displayed by the central room thermostat. With room thermostats assumed to measure a so-called reference temperature $T_{ref,i}$ = 0.75 $T_{air,i}$ + 0.25 $T_{rad,i}$ (see also section 3.3.3) it is a logical step to directly regulate the ideal heating system on that same reference temperature. By doing so, the evidence-based temperature settings of the behavioural model are transferred into the building energy simulation as truthfully as possible. Note that the ideal heater in `TRNSYS` can only regulate on the air temperature, requiring for every time step j the computation of the necessary air temperature $T_{air,i,j}$ yielding the desired reference temperature $T_{ref,i,j}$, given the mean radiative temperature of the previous time-step $T_{rad,i,j-1}$.

An unlimited heating power is supplied[5] and the radiative fraction of the ideal heating equipment is set to 0.3, corresponding to the use of convecto-radiators. Inevitably, whatever the radiative fraction chosen, the net energy demand is to a certain extent heating system dependent: changing the radiative fraction of the ideal heating under identical setpoint will change the net energy demand. However, by using the value of 0.3 for convecto-radiators, correspondence is again ensured with the aforementioned evidence-based set-point temperatures, collected from a representative sample of Belgian households of which more than 90 % report to heat by means of radiators/convectors (see Figure 3.18). It is believed that the so generated net energy demands are representative for actual heat demand, whatever the heating system used.

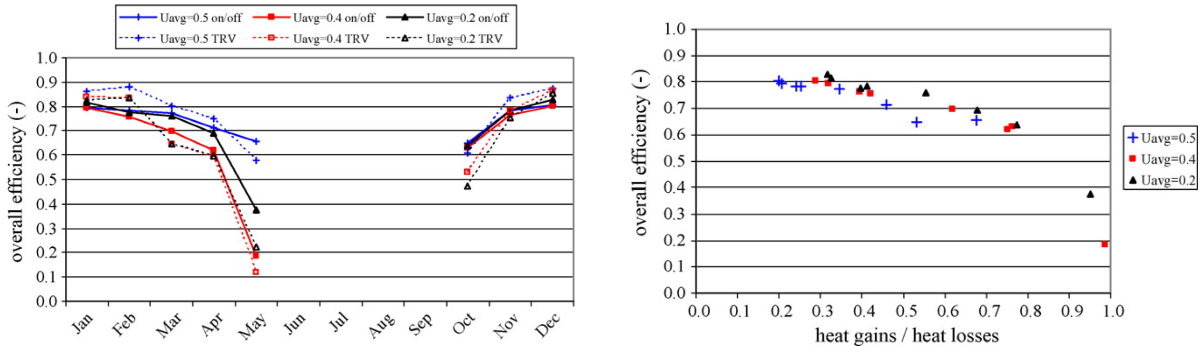
4.5.2 Overall heating system efficiency

Different standards are available estimating the overall heating system efficiency $\eta_{overall,heating}$, of which the European standard EN 15316-1 (2007) is the most elaborate. In the framework of the European Energy Performance of Buildings Directive, many national models have been developed based on the simplified methods described in this standard. In the current Energy Performance Regulation in Belgium for example, $\eta_{overall,heat}$ is defined once based on the characteristics of the entire space heating system and is then used as a constant value throughout the year. However, using a constant, annual efficiency is a rather strong simplification of reality, because it is found that the heating system efficiencies are far from fixed values but are instead highly dependent on the monthly varying degree of heating load (Bauer 1999, Peeters et al. 2008, Parys 2013).

In Peeters et al. (2008) for example, detailed simulations of the most widely used heating system in Belgium (high-efficiency or condensing gas boilers combined with radiators and central thermostat

[5]Limiting the heating power by means of the design heat load following prEN 12831 (2000) had negligible impact on the computed annual net energy demand.

and/or thermostatic radiator valves) have shown that the overall heating system efficiency strongly varies throughout the year - see Figure 4.7a.



(a) (b)

Figure 4.7: Monthly overall efficiency for three different insulated houses equipped with a modulating condensing boiler with fixed supply temperature set point and a room thermostat (on/off central emitter control) or thermostatic radiator valves (TRV). As a function of the months of the year (a) and, only for the room thermostat, as a function of the heat balance ratio (b). Source: Peeters et al. (2008)

The determining factor for the varying overall efficiency turned out to be the heat balance ratio γ, being the ratio of heat gains (solar and internal) over heat losses (transmission, infiltration and ventilation) - see Figure 4.7b. For low heat balance ratios (during winter period / poorly insulated dwelling) the overall efficiency can be quite high. For high heat balance rations (during spring or autumn / well insulated dwelling) it severely drops. Following Peeters et al. (2008), the reason for this is twofold: "*Firstly, low flow rates due to low heat demands cause higher relative electricity consumptions as pump and ventilator must work with low efficiencies. Secondly, due to the low heat demands, even a small heat delivery can easily result in indoor temperatures above the set points and thus more energy than strictly necessary is consumed*". Based on their results, regression based performance curves can be built and used to more accurately predict the monthly overall heating system efficiency as a function of the monthly heat balance ratio.

Similar work is done by Parys (2013), though only applicable to office buildings. In this work also, integrated simulation models including the building and HVAC systems were set up, after which regression models could be deduced for the monthly final energy use for heating, cooling and auxiliaries. Despite the large differences between office and typical residential heating installations, the results were similar to those of Peeters et al. (2008): the monthly efficiencies of emission, distribution and generation of heating (and cooling) all showed to be correlated quite well with the monthly heat balance ratio, with lower efficiencies being found at heat balance ratios representing lower part load ratios.

Finally, performance curves for the annual control and emission efficiency of water heating systems are also found in the German Standard DIN 4701-10 (2003) and the German guideline VDI 2067 (2000), both based on the simulation work of Bauer (1999). Here, the inverse of the efficiency is given in relation to the annual average relative heating load, i.e the ratio between the net energy demand and the maximal heating system output (boiler output capacity multiplied with time). This annual relative heating load is inversely proportional to the heat balance ratio. VDI 2067 (2000) states that "*the simplification of using curves leads to only negligible inaccuracies*".

The previous studies show how a large part of the complex interaction between building, inhabitant and dwelling can be accounted for with the simplified approach from Equation 4.14 by using simulation based performance curves. These curves allow to predict quite easily the overall or subsystem efficiency as a function of a representative and dynamic figure like the heat balance ratio. Unfortunately, studies providing such curves are scarce and often limited to certain heating systems. Nevertheless, an attempt is made to include them in the global modelling by following the next procedure:

- For high-efficiency or condensing gas boilers combined with radiators and central thermostat and/or thermostatic radiator valves, the monthly overall energy efficiency as a function of the monthly heat balance ratio is deduced from the regression models of Peeters et al. (2008) - see Figure 4.8.

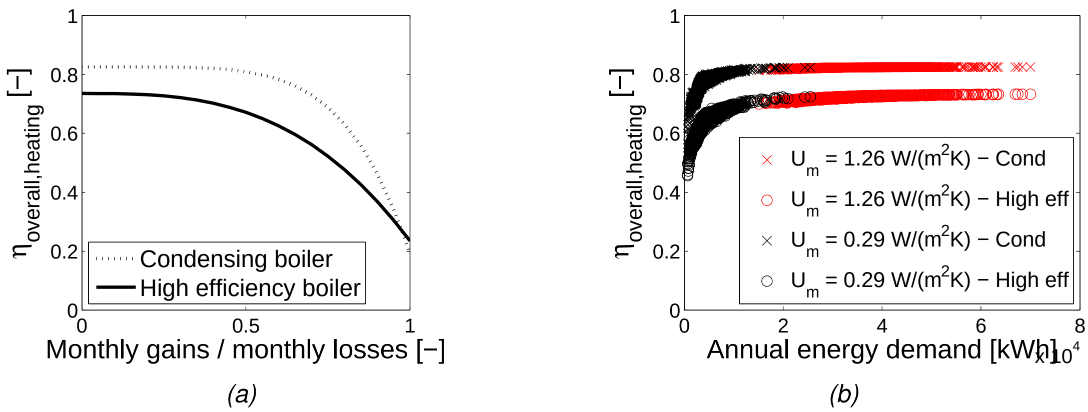


Figure 4.8: (a) The monthly heating system efficiencies as a function of the monthly gains over losses ratio (source: Peeters et al. (2008)) and (b) the resulting annual efficiencies as a function of annual net energy demand when applied on a poorly and a well insulated dwelling, inhabited by 3000 different users generated through Latin-Hypercube sampling of the probabilistic behavioural model of Chapter 3.

- For all other systems: an annual control and emission efficiency is calculated following VDI 2067 (2000). The annual production, storage and distribution efficiency is calculated following EN 15316-1 (2007) with default values taken over from the Belgian EPBD regulations.

4.6 Case study district Lijsterlaan

Throughout this dissertation, results are generated based on the same case study. This case study is described hereunder.

4.6.1 Description

The district case study is a small district in Leuven, Belgium, consisting of 52 almost identical dwellings built by the same building company around 1970. They are relatively large 2-storey dwellings with uninhabited attic, both in detached and in semi-detached typology. Some pictures and the original floor plans of the (detached) dwellings are given in Figure 4.9.

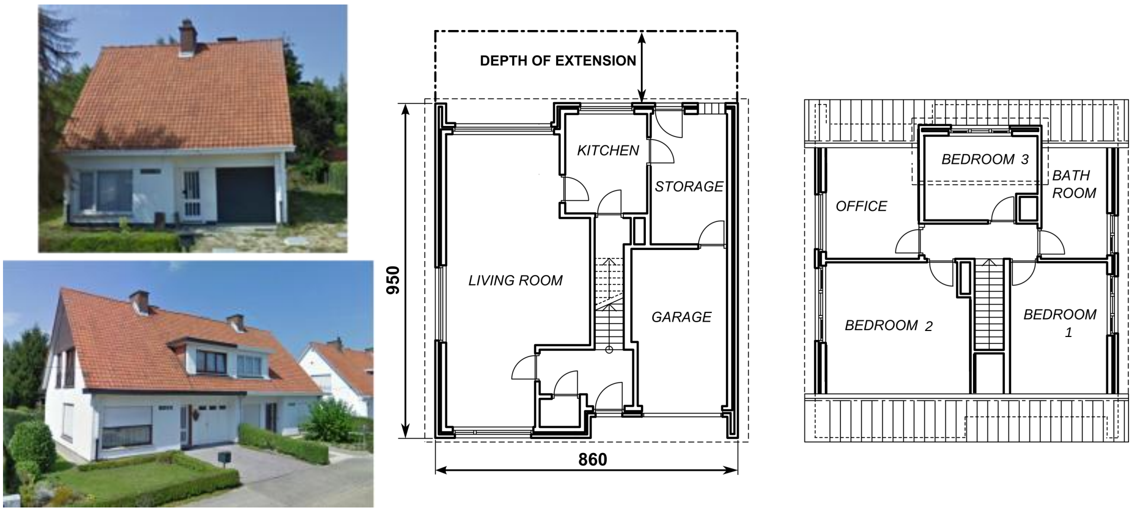


Figure 4.9: Casestudy dwellings: pictures (open and semi-terraced) and floor plans of ground and first floor of the open typology (dimensions in mm).

The total volume V is 432 m^3 and the gross floor area (including garage) is 162 m^2. Due to the limited floor area of the ground floor, many owners have enlarged the dwellings by adding a ground floor extension at the backside. Outer walls are cavity walls in brick. Both slab-on-ground and internal floors are concrete structures, while the pitched and flat roofs are wooden structures. All dwellings have a central hydronic heating system with gas boiler, radiators and a central room thermostat. None of the dwellings have a ventilation system (apart from the occasional ventilation grilles in the bathroom).

The detailed survey information of 10 randomly sampled dwellings is given in Table 4.4. The parameter $depth_{extension}$ depicts the building depth of the extension at the ground floor, as is shown in Figure 4.9. Although all dwellings were originally uninsulated, roof insulation (mineral wool) and cavity wall insulation (blown-in foam) is recently installed in most of them and original windows have been replaced by better performing ones. Also, the extensions tend to be of higher insulation quality than the original dwelling. The overall dwelling mean U-value, U_m [W/(m^2K)], varies between 0.76 and 1.34. The $U_m A_T / V = U_m / C$-value [W/(m^3K)] is also given, with V [m^3] the volume, A_T [m^2] the heat loss area and $C = V / A_T$ [-] the compactness. As a low compactness is associated with a less energy efficient dwelling, the $U_m A_T / V$-value allows for a more unequivocal comparison of the energy efficiency of dwellings with different typologies/geometries and insulation levels.

4.6.2 Composition of fictive set of dwellings

Although interesting by its variety, the subset is insufficient for use in this dissertation as the covered range of insulation levels is rather limited. Therefore, additional fictitious dwellings are composed

Table 4.4: Survey data of 10 individual dwellings

Dwelling number		1	2	3	4	5	6	7	8	9	10
Typology	(Semi)-Detached	D	D	D	D	D	S-D	S-D	S-D	S-D	S-D
orientation front facade		NW	SE	SE	SE	NE	SE	SE	SE	SE	SW
$depth_{extension}$	[m]	3.3	0	3.6	2.8	1.8	2.6	2.7	0	0	3.9
$d_{wall,PUR}$	[m]	0.04	0	0	0.06	0	0	0	0.04	0	0
$d_{wall,ext,PUR}$	[m]	0.04	-	0.04	0.08	0	0.07	0.05	-	-	0
$d_{roof,pitch,MW}$	[m]	0	0	0.05	0	0	0.13	0	0.12	0	0.10
$d_{roof,flat,MW}$	[m]	0	0	0	0	0	0	0	0.03	0	0.08
$d_{roof,ext,MW}$	[m]	0.13	-	0.09	0.18	0.04	0.15	0.18	-	-	0.08
$d_{ceilingAttic,MW}$	[m]	0.12	0	0.05	0.18	0.08	0	0	0	0	0.12
$d_{floor,PUR}$	[m]	0	0	0.03	0.06	0	0	0.03	0	0	0.03
$d_{floor,ext,PUR}$	[m]	0	-	0.03	0.06	0	0.04	0.03	-	-	0.03
$U_{glazing}$	[W/(m^{2}K)]	1.1	1.1	2.8	2.8	2.8	2.8	1.1	2.8	1.4	2.83
$U_{glazing,ext}$	[W/(m^{2}K)]	1.1	-	1.1	1.1	2.8	2.8	1.1	-	-	2.83
$\rightarrow U_m$	[W/(m^{2}K)]	0.85	1.26	0.85	0.75	1.32	1.06	1.03	1.04	1.31	0.96
$\rightarrow U_m A_T/V$	[W/(m^{3}K)]	0.69	1.02	0.70	0.61	1.08	0.74	0.72	0.72	0.91	0.68
n_{50}	[h^{-1}]	6	5.6	14.4	4.0	10.1	3.5	2.7	4.8	11	9.6
Condensing boiler?	[Yes/No]	Y	Y	Y	N	Y	Y	Y	N	N	N
Ventilation system	[-/A/C/D]	-	-	-	-	-	-	-	-	-	-

to allow for a better coverage of the total range in possible mean U-values −see Table 4.5. To do so, the geometry of the Lijsterlaan is taken over and the insulation thicknesses are varied to obtain a wider spread. In total 7 variants are constructed. As every insulation variant is duplicated for 3 different typologies (detached, semi-detached and terraced), 7 × 3 = 21 fictitious dwellings are obtained. For each of these, the extension depth and the orientation are randomly chosen between the discrete values given in Table 4.5. The extensions are assumed to take equal insulation thicknesses as the rest of the dwelling. Similarly as done in the housing stock approach of the TABULA-study (Cyx et al. 2011) different airtightness levels are assumed in accordance to the overall insulation

Table 4.5: Data of 3 × 7 = 21 fictitious dwellings

Fictitious dwelling number		1	2	3	4	5	6	7
orientation front facade		random [N - E - S - W]						
$depth_{extension}$	[m]	random [0 - 1.5 - 3]						
$d_{roof,MW}$	[m]	0	0.05	0.1	0.1	0.15	0.2	0.3
$d_{wall,PUR}$	[m]	0	0	0.05	0.05	0.05	0.1	0.15
$d_{floor,PUR}$	[m]	0	0	0	0.05	0.05	0.1	0.15
$U_{glazing}$	[W/(m^{2}K)]	5.68	5.68	5.68	2.83	1.1	1.1	0.70
$\rightarrow U_{m-example}$ *for detached and* $depth_{extension}$*=3m*	[W/(m^{2}K)]	*1.81*	*1.47*	*1.05*	*0.67*	*0.48*	*0.38*	*0.30*
$\rightarrow U_m A_T/V$	[W/(m^{3}K)]							
Detached		1.47	1.18	0.84	0.50	0.38	0.29	0.23
Semi-detached		1.24	1.04	0.81	0.45	0.32	0.25	0.19
Terraced		1.04	0.78	0.56	0.37	0.24	0.22	0.17
n_{50}	[h^{-1}]	15	15	10	6	3	1	0.6
Ventilation system	[-/A/C/D]	-	-	-	A	C	C	D
Condensing boiler?	[Yes/No]	N	N	Y	Y	Y	Y	Y

level : older/less insulated dwellings tend to be less airtight than newer/well insulated dwellings. For that same reason not all dwelling variants have a ventilation system. In old/less insulated dwellings, it might be assumed that ventilation will only occur by in-and exfiltration through the many air leakages and by the opening of windows. When shifting towards very well insulated and more airtight dwellings, the presence of a ventilation system becomes stringent, ranging from natural ventilation (A) to mechanical extraction (C) and balanced ventilation (D). The assignment of whether or not a fictitious dwelling has a ventilation system, and if so, which one, is done arbitrarily.

4.6.3 Implementation

For implementation in the building model, each dwelling is to be divided into a day- and a nightzone. Here, it is chosen to take the ground floor as dayzone and the first floor as nightzone. This is not entirely according to reality, since the ground floor contains the unheated garage and the first floor the frequently heated bathroom. Yet, by assuming both switched in position (bathroom to ground and garage to first floor), the overall heat loss of both situations can be assumed very similar. The influence of other zoning patterns will be further investigated in 5.3.5.

4.7 Conclusion

In this chapter the characteristics of the building energy simulation are described. The starting point is a two-zone building model in a transient simulation environment (`TRNSYS`), allowing for the intermittent and zonal heating of the probabilistic behavioural model. This building model is conceived as generic as possible, in the sense that it is easily adaptable and allows for a fast and straightforward generation of different dwelling typologies with varying insulation levels, air tightness levels, heating and ventilation systems etc.

The convective heat losses are modelled in a rather simplified way to reduce calculation time. The LBNL Infiltration model is used to assess the infiltration rates, requiring only the air permeability of the dwelling and the time-dependent wind speed and indoor-outdoor temperature difference. For the hygienic ventilation losses it is shown how neither the design guidelines nor the (Belgian) energy performance regulation provide reliable and realistic ventilation rates. Therefore, a pragmatic approach is followed in which the ventilation air change rates from a Belgian measurement campaign are directly taken over.

The net energy demand is computed via `TRNSYS` by means of an ideal heating equipment. An overall heating system efficiency, when possible based on simulation based performance curves, is then used to convert the demand to an energy use for space heating.

Finally, the case study dwellings and additional fictitious variants, all to be used in the following chapters, are briefly described.

5 Evaluation of methodology

The methodology developed in the two previous chapters, being a more realistic and probabilistic behavioural model in combination with a two-zone dynamic building model, has eventually been set up to allow for an improved prediction of the pre-retrofit energy use for space heating, thereby reducing the shortfall. The logical next step is to investigate if this methodology is indeed able to do better, and if so, to what extent.

5.1 Introduction

As the probabilistic behavioural model is mainly set up to be used on the aggregated scale (city, district, national, ..), evaluation should preferably be performed at that same level. Therefore, a full-scale validation at individual dwelling level makes only little sense. In Belgium, aggregated housing stock data is typically only available at national and regional level like e.g. the energy balance outcome of residential energy use in Flanders, one of the three regions in Belgium (EMIS 2015). However, it has never been the aim of this research work to actually build a (national) bottom-up housing stock model, implying that no aggregated simulation data can be generated to allow comparison. Therefore, another approach must be followed to get insight in the overall reliability of the previously developed behavioural and building model.

To do so, four different paths are followed in this chapter.

As starting point, the **probabilistic output for a specific dwelling**, generated when the behavioural model is imposed, is **briefly analysed** (5.2). These findings will prove worthwhile throughout the rest of this chapter. At the same time, it is investigated how many simulation runs per dwelling are minimally required to reach a satisfying convergence.

Secondly, an **uncertainty and sensitivity analysis** is performed (5.3), allowing to evaluate the behavioural model and get insight in its most important and critical parameters. Also, the so obtained sensitivities can be compared to values of other residential building models found in the literature. Finally, the influence of different zoning patterns on the computed outcome and sensitivities will be investigated.

Thirdly, a **comparison of the computed output with measurements** is carried out (5.4). To do so, the case study Lijsterlaan dwellings are used, described in the previous chapter and intensively monitored during the winterperiod 2012-2013. Afterwards, the fictitious Lijsterlaan dwellings are added to obtain a larger sample and allow comparison with large-scale Belgian measurement campaigns. It must be stressed that the comparison with measurements is not to be seen as a rigid validation of the method, in the literal sense of the word, yet rather as a measure to check if indeed realistic energy uses are predicted.

Finally, the methodology is evaluated through the **comparison with the Belgian energy performance assessment calculation** (5.5). The latter is frequently used as energy saving prediction method, even for policy making (see e.g. Van der Veken et al. (2013)) and despite the fact that it systematically overestimates actual energy use (Hens et al. 2010). By comparing both methods, it is investigated to what extent the here developed methodology is able to do better.

5.2 Output analysis for two fictitious dwellings

To get insight in the probabilistic output spread caused by the behavioural model, both a poorly (U_m = 1.24 W/(m^{2}K)) and a well (U_m = 0.27 W/(m^{2}K)) insulated dwelling are chosen, being fictitious dwellings 1 and 7 from Table 4.5 in detached typology[1]. A reference output is computed by generating a (non-space-filling) Latin Hypercube sampling scheme of 3000 runs for 13 behavioural input parameters and imposing it in both dwellings. This reference output is analysed first (5.2.1). As it is of course unfeasible to run 3000 simulations every time a dwelling needs to be analysed, it is investigated afterwards which minimal sample size is needed to reliably reproduce the reference output (5.2.2).

Throughout this dissertation, two outputs are of interest and will be handled for in this section: the total heating season energy use for space heating $E_{tot,use}$ and the indoor temperature, reflected in the daily mean reference temperature $T_{ref,i}$ = 0.75 $T_{air,i}$ + 0.25 $T_{rad,i}$ at T_e = 5 °C. The latter is obtained after averageing all daily mean reference indoor temperatures over all days where the daily mean outdoor air temperature is within the range of [4.5 ; 5.5] °C. For the Meteonorm climate file of Ukkel, Belgium, as used in the TRNSYS-simulations, this condition is fulfilled for 20 days within the total heating season.

[1] For reasons specific to the sensitivity analysis in 5.3, the insulation thicknesses of fictitious dwelling 1 are taken equal to 0.02 m here already (instead of 0.0 m from Table 4.5). Also, the orientation of front facade of both dwellings 1 and 7 is set to 150° (~ NNW) and the depth of the extension is set to 3m. By doing so, the datasets generated here can be re-used for the sensitivity analysis.

5.2.1 Analysis of the reference output

Here, only a preliminary analysis of the reference output is carried out, permitting to get a first view in how the behavioural model determines the probabilistic output distribution of a dwelling. A further in-depth insight will result from the following sections in this chapter.

Energy use for space heating

The energy use for space heating of both dwellings is given in Figure 5.1. Both distributions show a positive skewness (= the right tail is longer than the left tail) and are best fitted with a lognormal distribution. The impact of the behavioural model is immediately visible: it generates a wide spread around the mean value. The [10^{th}, 90^{th}] percentile interval, containing 80 % of all possible output values, equals [0.77 , 1.28] times the mean energy use in the poorly insulated dwelling and [0.59 , 1.52] times the mean energy use in the well insulated dwelling. So, if one does not know who is to inhabit the dwelling, important deviations are possible in estimating the energy use. Also, when translated into a coefficient of variation $C = \sigma/\mu$, being 0.21 and 0.46 for the poorly and well insulated dwelling respectively, it is clear how the behavioural model induces a higher output variability, at least in relative terms, in the well insulated dwelling than it does in the poorly insulated dwelling.

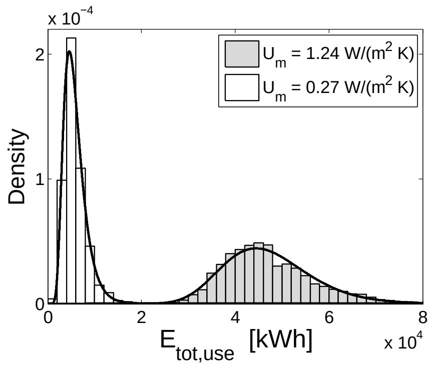


Figure 5.1: Impact of the behavioural model: frequency distribution of the total energy use for space heating (with fitted lognormal distribution), based on the 3000 calculations of a poorly (U_m = 1.24 W/(m^2K)) and a well (U_m = 0.27 W/(m^2K)) insulated dwelling.

Daily mean indoor temperature at T_e = 5 °C

Three different daily mean temperatures are analysed: the dayzone ($T_{ref,day}$) and nightzone ($T_{ref,night}$) temperature and the volume weighted mean of both, being the dwelling mean temperature ($T_{ref,dwelling}$). The frequency distributions are given in Figure 5.2.

As expected, the dayzone experiences the highest temperatures, the nightzone the lowest and the dwelling temperatures in between. It is clear that it makes no sense in searching an analytical fit for the nightzone temperature of the poorly insulated dwelling. The reason is the strong influence of the nightzone heating behaviour. When decomposing the 3000 users into the three categories of PATTERNNIGHT, the cumulative frequency curves of Figure 5.3 are obtained. For $T_{ref,night}$ of the poorly insulated dwelling, it is visible how the first part of the cumulative curve is mainly composed

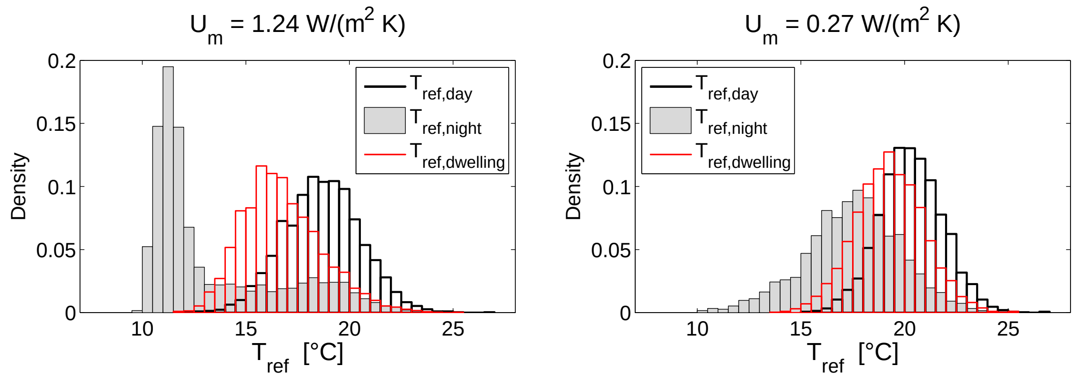


Figure 5.2: Frequency distributions of the reference indoor temperature at T_e = 5 °C, based on the 3000 calculations of a poorly (U_m = 1.24 W/(m^{2}K)) and a well insulated (U_m = 0.27 W/(m^{2}K)) dwelling.

of households who never heat the nightzone. For these households the nightzone temperature is almost exclusively determined by the outdoor conditions and insulation quality and therefore converges to a small range −see also to the large peak around [12-13] °C of Figure 5.2. Conversely, the flatter second part of the cumulative curve contains the households who do heat the nightzone to a greater or lesser extent, making the nightzone temperature strongly dependent on the user behaviour −see long right tail of Figure 5.2. While the impact on the temperature cumulative curve is very pronounced, the corresponding influence on the dwelling's energy use is less distinct.

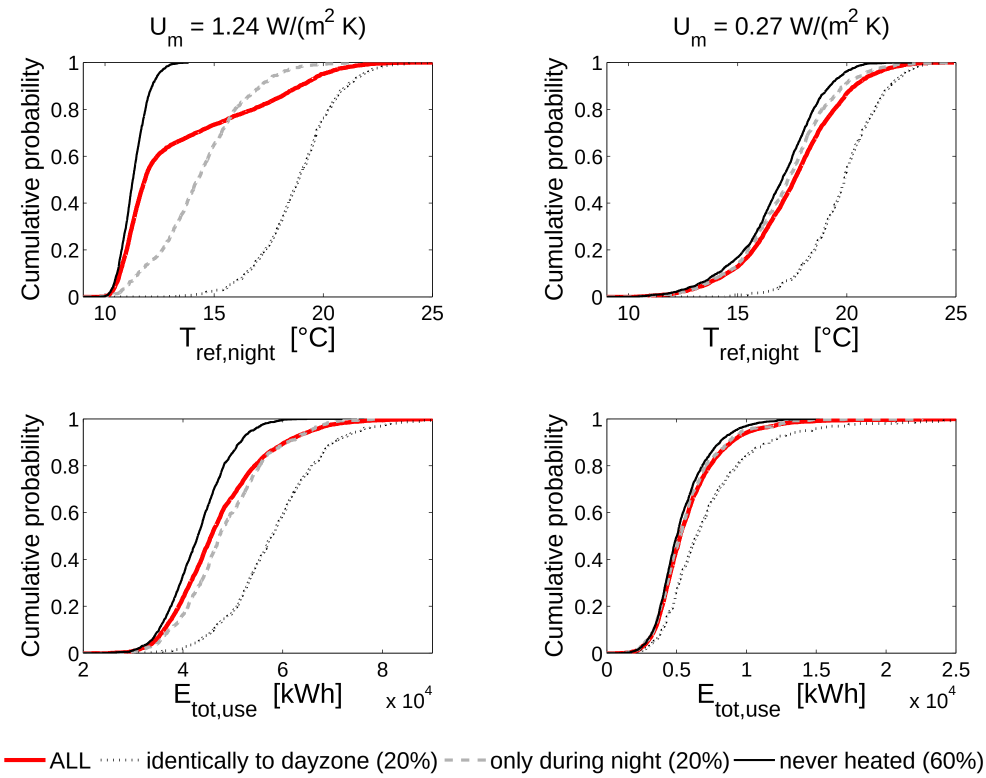


Figure 5.3: Influence of the three nightzone heating patterns of PATTERNNIGHT on the reference nightzone temperature (top row) and the total energy use for space heating (bottom row), for a poorly insulated dwelling (left) and a well insulated dwelling (right).

For $T_{ref,night}$ of the well insulated dwelling, the impact of PATTERNNIGHT is clearly lower. The cumulative temperature curves of never heating the nightzone or only doing so during night even prove to be almost identical. Due to the high insulation level of this dwelling, both patterns are virtually equal. The required setback temperatures during night are easily obtained either without heating through the utilization of the incident gains (both solar and occupant-related) either with a very limited amount of additional heating, making also the energy use curves of both patterns almost identical.

5.2.2 Sampling convergence

As said, it is unfeasible to calculate 3000 simulation runs whenever a dwelling needs to be analysed. Instead, a space-filling Latin Hypercube sampling scheme is chosen, allowing for less simulation runs and a still reliable coverage of output space. When using such sampling scheme, compared with the basic random sampling scheme, far lesser runs are needed to obtain the same accuracy (Janssen 2013, Van Gelder 2014). Yet, no general recommendations can be given about how many sample runs are required. All depends on the problem itself and on which output parameter is considered. While Macdonald (2009) states that "*for practical purposes in typical building simulation applications, Monte-Carlo uncertainty analysis should use about 100 runs and simple random sampling.*", contraindications for that statement are found in Janssen (2013). The dependence on the kind of output parameter considered is shown by Parys (2013): while the indoor temperature profile of an office building could be satisfyingly estimated within 100 runs, twice as much runs were required to reliably assess summer comfort using the number of weighted exceeding hours.

Therefore, it is investigated here, for a poorly and a well insulated case study dwelling, how many simulation runs are minimally required to reach a satisfying convergence regarding the annual energy use for space heating and daily mean indoor temperature $T_{ref,i}$. It must be stressed that the results apply to this particular case study and output parameters, and should not be interpreted as general guidelines.

Methodology

The reference output from above serves as the baseline against which all outputs with lesser runs per dwelling will be compared. The sampling convergence of 4 different sample sizes is investigated: 50, 100, 150 and 200 runs. To reduce calculation time the following procedure is adopted. 10 different LHS space-filling sampling schemes are generated, each containing 25 runs for 13 stochastic behavioural parameters. These 10 sampling schemes are imposed to both dwellings only once, resulting in 10x25 output values per dwelling. Elementary combinatorics are then used to compose the sample sizes as multiples of 25 runs. For example, the 100=4x25 runs are composed by taking out k(=4) sets out of the total n(=10) sets, called a *combination C*. This means that $C(n,k) = \frac{n!}{k!(n!-k!)}$ = 210 unique combination sets of 100 runs can be constructed. Given that $C(n,k) \equiv C(n,n-k)$, the following amount of unique combination sets are composed for the sizes 50=2x25, 100=4x25, 150=6x25 and 200=8x25 respectively: 45, 210, 210 and 45.

Four statistic measures are calculated for all combination sets: the (arithmetic) mean, the 10th, 50th (median) and 90th percentile. To assess the accuracy of any combination set j in comparison with the reference output, the relative deviation δ_j is assessed for every statistic measure. For example, the relative deviation $\delta_{j,mean}$ of the mean $\overline{x}$ for a particular combination set of output data Y_j equals

$$\delta_{j,mean} = \frac{\overline{x}_{Y_j} - \overline{x}_{ref}}{\overline{x}_{ref}} \tag{5.1}$$

The lower these relative deviations for a certain sampling size, the higher the sampling convergence and the more one can trust that this sample size is able to reliably capture the reference output.

The above procedure offers a safe and rather conservative estimation of the sampling convergence. The procedure assesses the convergence of combinations of k different space-filling schemes of 25 runs. The main advantage is the limited calculation time, since only 10x25 = 250 simulations runs are needed per dwelling to offer the basic sets. Any combination of k schemes is however very likely to cover the total parameter space less optimally than a single space-filling scheme of kx25 runs. So, if relative deviations are found to be small for a certain sample size when following the above procedure, they are very likely to be even smaller when a single space-filling sampling scheme of the same sample size is used −as will be the case throughout the rest of this dissertation.

The results for $E_{tot,use}$ and $T_{ref,i}$ are discussed separately hereunder.

Energy use for space heating

Figure 5.4 shows the relative deviations of the total energy use for space heating for the 4 statistic measures and for all 4 sample sizes. The following conclusions can be drawn:

- *Mean is very well predicted*
  Even a small sample size of 50 is sufficient to predict the mean value within an accuracy of more than 5 %. Once a sample size of 200 is used, all deviations are lower than 1 %.
- *Median is quite well predicted*
  For the median value, more runs (100 to 150) are needed to guarantee an accuracy of 5 %. Once a sample size of 200 runs is used, the relative deviations are also close to 1 %.
- *Tails are more difficult to predict*
  Due to the lognormality of the output data, the left tail of the distribution is shorter and steeper than the right tail, leading to slightly more robust estimations of the 10th than the 90th percentile −certainly for the poorly insulated dwelling. Again, in comparison with the mean, more runs are needed to estimate the tails reasonably well.
- *Difference between both insulation levels of dwelling*
  The well insulated dwelling tends to have larger deviations under the same sampling size, due

to its larger output variability compared to the poorly insulated dwelling (see above). The larger the output variability, the more difficult to predict it.

Overall, to reliably capture not only the mean and median but also the tails of the energy use for space heating, a sample size of 200 runs per dwelling is adopted in this work.

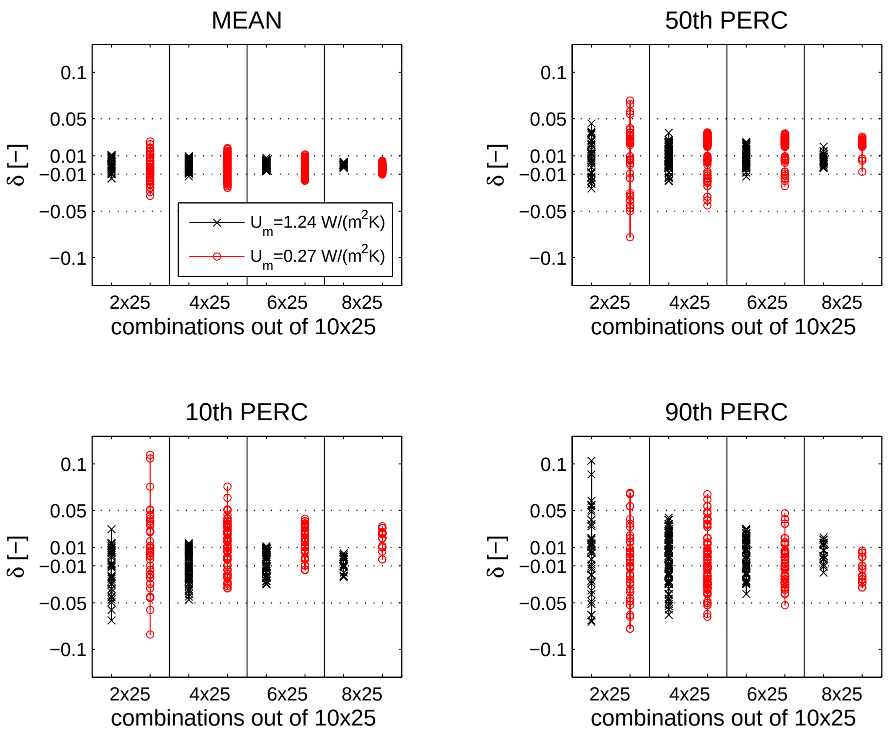


Figure 5.4: Total heating season energy use for space heating: relative deviation δ of the output statistics of each set against the reference output statistics, for a poorly insulated dwelling (black) and a well insulated dwelling (red).

Daily mean indoor temperature at T_e = 5 °C

The relative deviations for dayzone, nightzone and dwelling are shown in Figure 5.5, 5.6 and and 5.7.

Compared with the energy use for space heating, convergence occurs much faster for the indoor temperatures. For the dayzone temperature 50 simulations is already a sufficient amount to estimate all statistic measures within ±5 % accuracy. Because of the larger variability in nightzone temperatures more runs are needed. For example, due to the large right tail of the $T_{ref,night}$ distribution in the uninsulated dwelling (Figure 5.2), the 90th percentile is much more sensitive to the sample size. Yet, as soon as 150 runs are adopted, all errors remain within the ±5 % band. Also, with the left tail of the well insulated dwelling being more spread compared to the poorly insulated dwelling, it is no surprise that more runs are needed to reliably estimate the 10th percentile of $T_{ref,night}$ in the former. As expected the convergence of the dwelling temperatures is a mixture of the above. Overall within this work, a limited amount of 100 and even 50 runs could do to reliable estimate the daily mean indoor temperatures. Again, as found by Parys (2013), these low sample sizes do not hold when one is interested in for instance assessing summer comfort, in which temperature peaks must be well captured, instead of the daily mean indoor temperature considered in this work.

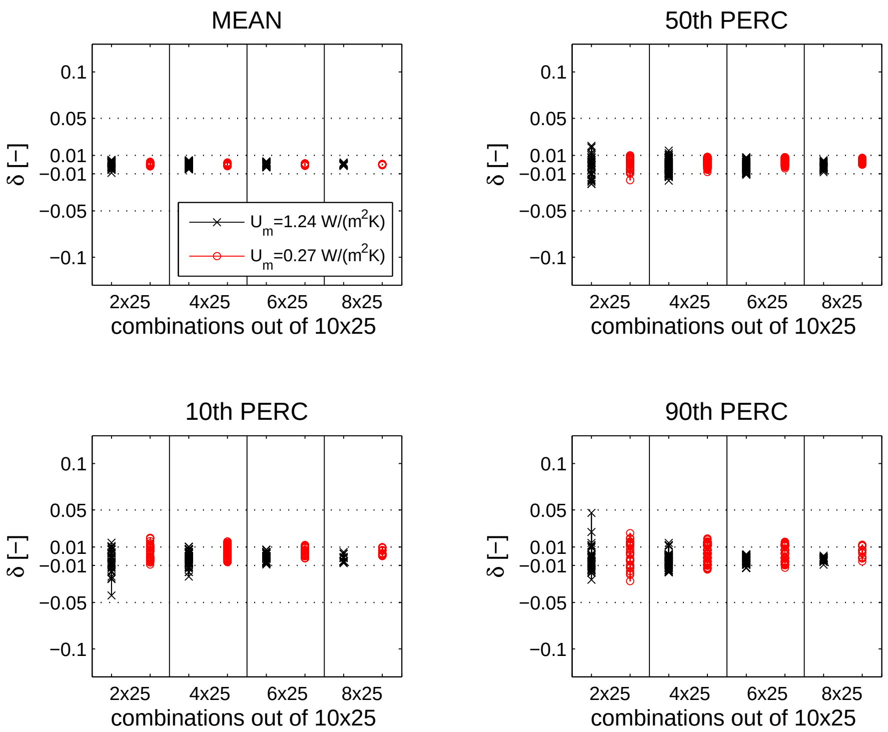


Figure 5.5: DAYZONE daily mean indoor reference temperature $T_{ref,i}$ at T_e=5 °C: relative deviation δ of the output statistics of each set against the reference output statistics, for a poorly insulated dwelling (black) and a well insulated dwelling (red).

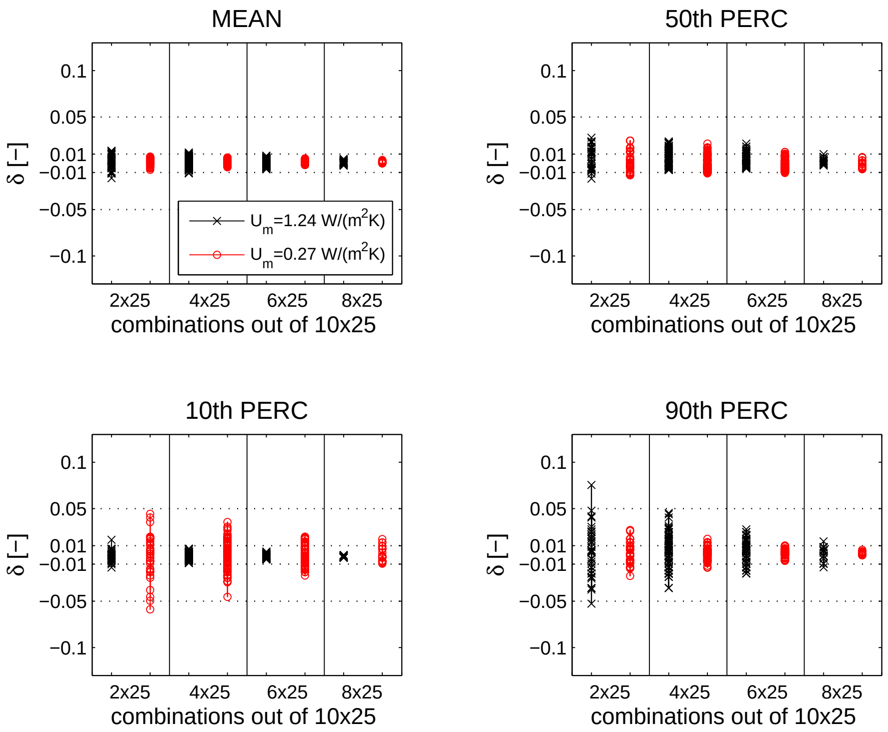


Figure 5.6: NIGHTZONE daily mean indoor reference temperature $T_{ref,i}$ at T_e=5 °C: relative deviation δ of the output statistics of each set against the reference output statistics, for a poorly insulated dwelling (black) and a well insulated dwelling (red).

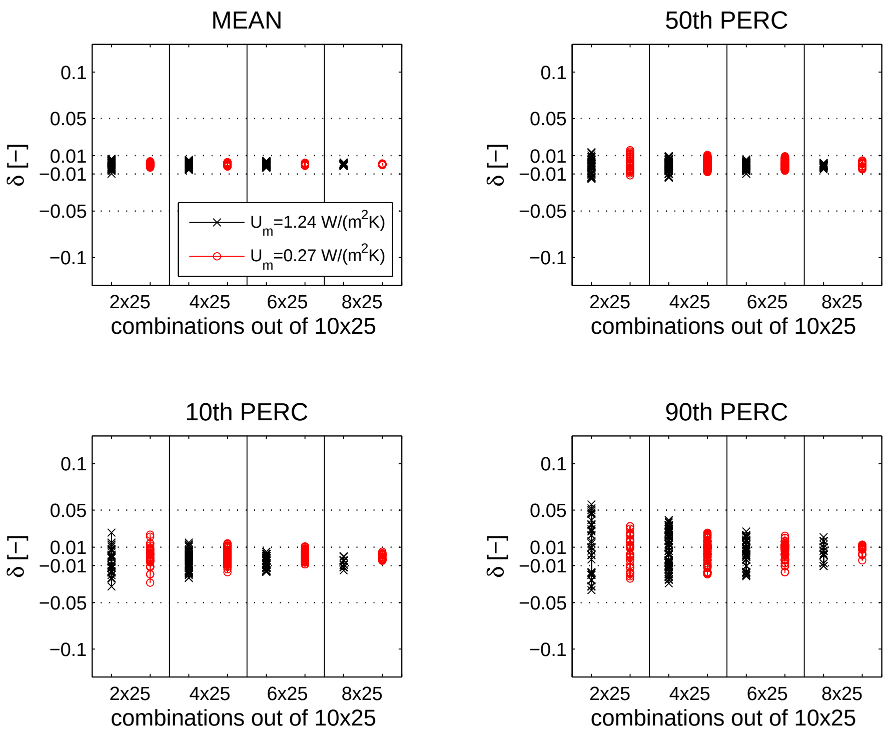


Figure 5.7: DWELLING daily mean indoor reference temperature $T_{ref,i}$ at T_e=5 °C: relative deviation δ of the output statistics of each set against the reference output statistics, for a poorly insulated dwelling (black) and a well insulated dwelling (red).

5.3 Sensitivity and uncertainty analysis

It is important to first mention the difference between sensitivity and uncertainty analysis, as both terms make use of the same sampling and analysis methods and are therefore often used interchangeably. As stated by Macdonald (2002) "*The aim of a sensitivity analysis is to discover the (typically few) input parameters to which the measured output of a model is sensitive, i.e. a change in a design parameter (say 1 % less infiltration) would result in a relatively larger change in a performance metric (say 10 % less heating energy required). A crucial aspect of a sensitivity analysis is that it is unnecessary to quantify the likely variation in the model's parameters. Conversely, in an uncertainty analysis the variation in the input parameters is critical to the analysis, as the aim is to discover the likely variation in the output due to the actual variations in the input. A side effect of this is that the model may be sensitive to a specific parameter but, if the parameter is well known, it is not a critical parameter in an uncertainty analysis.*"

In this section, a *sensitivity* analysis is performed to see how small changes in the behavioural and building parameters affect the total energy use for space heating. To do so, the multiple linear regression method is used. The so obtained sensitivity indicators allow to see how the behavioural parameters compare to the building parameters in terms of output sensitivity (are they equally important or is the total energy use far more sensitive to the behavioural parameters than to the building parameters?). Also, if the energy use proves to be very sensitive to behavioural parameters of which the input uncertainty is large (for example the heating behaviour in the nightzone, reflected in PATTERNNIGHT), future work should be put in gathering data reducing these uncertainties. Finally, the sensitivity indicators can be compared with the literature values, revealing to what extent the here developed building and behavioural model correspond to more simplified residential building models.

In complement an *uncertainty* analysis is performed for the behavioural model by means of Spearman's rank correlation coefficients. This technique allows to reveal which behavioural parameters contribute the most to the output variability, being the total energy use, given the best possible estimates for the input variability, being the behavioural model developed in Chapter 3. Conversely to the previous multiple linear regression, the uncertainty indicators are now input distribution dependent. Therefore, assessing likely input variabilities for the building parameters is not done here, as in the current context the dwelling parameters are conceived deterministically and well-known (known geometry, known insulation thickness, known infiltration air change rates etc.). Assuming input variabilities of any kind would be an arbitrary procedure and does not render useful output for the uncertainty analysis. An additional advantage of the Spearman's rank correlation coefficients is that the sensitivity indicators of the categorical variables (like for example PATTERNNIGHT) can be directly compared to those of the numerical variables (like TSETPOINT), a comparison that is not possible when using the multiple linear regression.

Even though not incorporated in the uncertainty analysis, the deterministic dwelling parameters do have an influence on the outcome, as it is expected that a well insulated dwelling will be differently sensitive than a poorly insulated one. Hence, two Lijsterlaan dwellings are analysed simultaneously: the poorly insulated fictitious dwelling 1 and the very well insulated fictitious dwelling 7, both in detached typology.

First, a brief literature overview is given of typical techniques for and outcomes of sensitivity and uncertainty analysis performed on residential building models. Second, it is shortly described how the datasets, serving as input for both analyses, are generated. Third, the sensitivity and uncertainty analysis are performed, followed by a concluding paragraph.

5.3.1 Literature Review

Different methods exists to perform either an uncertainty or sensitivity analysis, classified into one-at-a-time, screening, correlation-based, segmentation-based and variance-based methods (Janssen et al. 2013). One-at-a-time and screening methods are local methods, in which each of the parameters is altered separately whilst keeping all other parameters fixed. Many other methods, called 'global' methods, rely on more advanced sampling schemes, in which all parameters are altered simultaneously, thereby incorporating possible dependencies between parameters (Macdonald 2002). Almost all techniques are suitable both for uncertainty and sensitivity analysis. For a more elaborate overview of the different methods and techniques available, the reader is referred to Lomas and Eppel (1992), Macdonald (2002), Janssen et al. (2013). Whatever method used, they typically lead to (relative) sensitivity indicators, allowing for an ordering of the input parameters from most to least important.

Brohus et al. (2009) performed a screening analysis on a semi-detached dwelling, following the Elementary Effect Method, better known as Morris method (Morris 1991). The 4 most important parameters defining the yearly heating energy consumption proved to be the set-point temperature for space heating, the amount of occupied hours per day, the appliances heat load and the U-value of the windows. The building heat capacity and the infiltration were the least influential. The same Morris method was applied by Corrado and Mechri (2009) on the net energy demand for space heating of a family house case study, in which 105 input factors were altered. The indoor temperature, the air change rate, number of occupants, conductivity of the external wall insulation and metabolic and equipment heat gains were the most important ones (in decreasing order of importance). Booth et al. (2011) also used the Morris method on their quasi-steady state energy model of a residential flat and identified the fraction of space heated, the internal heating set-point temperature, the coefficient of performance to be the most dominant parameters. A global uncertainty analysis was performed by Doloisy et al. (2010). They used the multiple linear regression technique on samples generated with a Latin-Hypercube sampling design to deduce standardized regression coefficients. Again, the energy use for space heating was mostly influenced by the temperature setpoint in the dayzone (after the outdoor temperature), followed by the infiltration rate and the heating floor water set-point.

The previous uncertainty analysis all relied on input distributions gathered from measurements, surveys, the literature, theoretical considerations and sometimes also educated guesses. Yet, a preliminary screening of the parameters can also be carried out without any knowledge of input distributions, simply by inducing small changes to each of the input parameters. Such a local sensitivity analysis was carried out by Firth et al. (2010) on a building stock model by varying 27 primary input parameters. The final sensitivities were the weighted average values of all 47 house archetypes. The heating demand temperature resulted in the highest normalized sensitivity (+1.55), which can be interpreted as 1.55 % increase in the CO_2 emissions of an average dwelling result due to a 1 % rise in the heating demand temperature. The length of the daily heating period (+0.62) and the external air temperature (-0.58) were the second and third most important parameter. The same procedure was followed by Cheng and Steemers (2011) and Kavgic et al. (2013) on their own respective building stock models, leading to remarkably similar sensitivities as Firth et al. (2010).

An important finding emerging from the previous overview is the consist impact of the indoor temperature on the predicted energy use −independently of the method chosen or the case study involved and whatever definition of indoor temperature is adopted (either the overall mean internal temperature or the heating set-point temperature at times of heating). Apart from this indoor temperature, there is only little consistency between the different studies concerning the other dominant parameters. All of course depends on which parameters are taken into account in the analysis and which are not (e.g. if outdoor temperature is included, it shows to have dominant impact), but also on the input distributions used (the larger the adopted uncertainty ranges of the input, the more it can contribute to the output uncertainty), the properties of the case study dwelling (a well insulated dwelling can be differently sensitive than a poorly insulated dwelling) and the characteristics of the building model used (highly simplified against complex). The outcome of an uncertainty/sensitivity analysis thus proves to be very case-specific, making it difficult to solely rely on the outcome of other studies. Therefore, it is indeed worthwhile to perform our own analysis, identifying those input parameters to which the estimated energy use is most sensitive to within the framework of the developed behavioural and building model.

5.3.2 Input distributions

Datasets are constructed by sampling the input parameters $X_{i=1..p,k}$ for every run k, computing the corresponding output Y_k and repeating this for several runs k= 1...n. In order to cover a sufficiently wide range of input parameters and generate a reliable set of output values, a non-space-filling Latin-Hypercube scheme is generated, providing in the sampling of p input parameters and n = 3000 simulations per dwelling. The input distributions from which is to be sampled, are given hereunder.

Behavioural parameters

The behavioural parameters are those from the probabilistic behavioural model. Each of these 13 parameters and their respective input distribution can be found in Table 3.17 and are entirely adopted here.

Two comments must be made. Firstly, even though DELTAT is sampled in the behavioural model, it is the resulting setback temperature TSETBACK = TSETPOINT - DELTAT that will be used in the following sensitivity and uncertainty analysis. In terms of the effect on the energy use for space heating, TSETBACK has a direct physical meaning (low setback temperatures are expected to lead to lower energy uses), whereas DELTAT is always to be interpreted in relation to the setpoint temperature itself. Secondly, the two last categories of the categorical variable WHENSETBACK are modelled identically in the behavioural model (see Table 3.7) and are thus taken together in the following analyses.

Building parameters

Only for the multiple linear regression of the sensitivity analysis perturbations are generated in the otherwise deterministic input values of the building model. As a multiple linear regression coefficient is to be interpreted as a partial derivative (see further), the exact nature of these perturbations is of negligible importance. The input values of both fictitious dwellings are picked from a uniform distribution within a small symmetric range around the nominal input value, shown in Table 5.1. Note that the depth of the extension and the building orientation of both dwellings are now taken equal (instead of randomly determined in Table 4.5) to allow for a fair comparison. Also the heating efficiency is taken equal for both dwellings, corresponding to the value of a high-efficiency boiler combined with radiators and central room thermostat (see Figure 4.8).

Table 5.1: Uniform variation of the dwelling input parameters for a poorly (U_m = 1.24 W/(m^{2}K)) and a well (U_m = 0.27 W/(m^{2}K)) insulated fictitious dwelling.

Dwelling variant number		*Range*	*Initial input values*	
			Dwelling 1	*Dwelling 7*
			U_m = 1.24 W/(m^{2}K)	*U_m = 0.27 W/(m^{2}K)*
orientation front facade	[°]	±20	150[a]	150[a]
$depth_{extension}$	[m]	±1	3[a]	3[a]
$d_{wall,PUR}$	[m]	±0.01	0.02[a]	0.15
$d_{roof,MW}$	[m]	±0.01	0.02[a]	0.30
$d_{floor,PUR}$	[m]	±0.01	0.02[a]	0.15
$U_{glazing}$	[W/(m^{2}K)]	-	5.68	0.86
n_{50}	[h^{-1}]	±20%	15	0.60
n_{vent}	[h^{-1}]	±20%	-	0.25
$\eta_{vent,heatRecovery}$	[-]	±20%	-	0.7
$\eta_{overall,heat}$	[-]	±0.05	0.7[a]	0.7[a]

[a]Different value from Table 4.5

Due to the properties of the developed building model and the desired output of the sensitivity analysis for this research, the variation in dwelling input parameters is restricted in 3 ways:

- **Window properties cannot be altered**
  In many sensitivity analyses on building models, the influence of the window properties is investigated by simply changing the U- or g-value in the model. However, TRNSYS does not allow to easily perform minor changes to the U- or g-value of the window glazing, as both values are internally calculated based on the dimensional and optional properties of the glazing panes, the gas type between the panes, the slope of the window etc. Therefore, the window U- or g-value is not included in the sensitivity analysis. As the U-value has shown to be a relatively important parameter (Firth et al. (2010), Cheng and Steemers (2011), Kavgic et al. (2013)), its absence in the sensitivity analylsis must be kept in mind when interpreting the final results.
- **Initial values of zero are avoided**
  Typically, a sensitivity analysis is performed by imposing small changes in both positive and negative directions around the initial input values. The poorly insulated dwelling initially has no insulation present, meaning that small changes would only be possible in the positive direction, impeding a proper comparison with the well insulated dwelling. Therefore, it is chosen to use a 2 cm thickness as initial insulation thicknesses of dwelling 1, both for the uncertainty and sensitivity analysis.
- **Independent heating system efficiency value**
  When using the efficiency curves of Peeters et al. (2008) the overall heating system efficiency is a clear function of net energy demand (see Figure 4.8). This implies that the efficiency is not an independent input parameter, but is in itself defined by the characteristics of both dwelling and user. This is of course not desired in a robust sensitivity analysis. Therefore, for the application of the sensitivity analysis in this section, a fixed heating system efficiency is used for both dwellings and altered within a uniform range.

5.3.3 Sensitivity analysis: multiple linear regression coefficients

For the sensitivity analysis the datasets are generated by sampling 13 behavioural and 8 dwelling parameters, leading to a total sampling scheme of $p = 13 + 8 = 21$ parameters in $n = 3000$ runs. The same sampling scheme is used for both dwellings.

Technique: multiple linear regression

In multiple linear regression a linear relationship is modelled between the dependent variable Y, being the total energy use for space heating [kWh], and the independent variables $X_{i=1...p}$, being the behavioural and dwelling input parameters. Since Y proved to be skewed, it is transformed to $\log Y$. This results in a normal and thus more symmetric distribution of the dependent variable and is preferred in a linear regression analysis. The following regression model can then set up:

$$\log Y = C + \sum_{i}^{p} \beta_i X_i \tag{5.2}$$

with C the constant intercept term. When taking the partial derivative in X_i of both sides of the equation, the interpretation of the regression coefficient β_i becomes clear:

$$\frac{\partial}{\partial X_i}(\log Y) = \frac{\partial}{\partial X_i}(C + \sum_{i}^{p} \beta_i X_i) \Leftrightarrow \frac{1}{Y}\frac{\partial Y}{\partial X_i} = \beta_i \Leftrightarrow \frac{\partial Y/Y}{\partial X_i} = \beta_i \tag{5.3}$$

$100\times\beta_i$ is thus equal to the percentage change in Y due to an increase of X_i with one unit, with all other parameters held constant. β_i can thus be interpreted as the 'partial' slope of the multi-dimensional plane in X_i. As it is difficult to compare these coefficients due to different units, a normalizations is first performed by dividing every independent variable X_i by its mean value μ_{X_i}, so that $\hat{X}_i = X_i/\mu_{X_i}$. When taking again the partial derivative,

$$\frac{\partial}{\partial X_i}(\log Y) = \frac{\partial}{\partial X_i}(C + \sum_{i}^{p} \hat{\beta}_i \hat{X}_i) = \frac{\partial}{\partial X_i}(C + \sum_{i}^{p} \hat{\beta}_i \frac{X_i}{\mu_{X_i}}) \Leftrightarrow \frac{\partial Y/Y}{\partial X_i/\mu_{X_i}} = \hat{\beta}_i \tag{5.4}$$

it is clear that $\hat{\beta}_i$ can now serve directly as a relative sensitivity indicator since is to be interpreted as the percentage change in Y due to an increase of X_i by 1 % of its mean value, with all other parameters held constant. Note that $\beta_i = \hat{\beta}_i/\mu_{X_i}$.

It is not possible to calculate these sensitivity indicators for the categorical variables, as a small change of say 1 % in a categorical variable has no meaning. Still, the categorical variables from the behavioural model can and should be included in the multiple linear regression model, since otherwise, a large part of the variability of the output could remain unexplained, leading to a low performance of the regression model. To do so, the categorical variables need to be transformed to dummy variables. Every categorical variable $X_{i,cat}$, containing C categories, is represented by $C-1$ dummy variables $D_{j,c}$ with $c = 1 \ldots C-1$. The omitted category functions as the reference category. The final regression model then looks like this:

$$\log Y = C + \sum_{i} \hat{\beta}_i \hat{X}_i + \sum_{i,cat}(\sum_{c}^{C-1} \alpha_{j,c} D_{j,c}) \tag{5.5}$$

with the regression coefficient $\alpha_{j,c}$ now to be interpreted as the percentage change of Y when changing from the reference category to category c of categorical variable $X_{i,cat}$, with all other parameters remaining unchanged.

The coefficients of the final regression model are given in Table 5.2. Note that the household variables NUMOCC, AGECAT and ACTIVITY have been left out of the final model. They proved to have no or only few and low coefficients significantly different from zero at the α=0.01 level and due to their mutual correlations and their correlations with other variables, they take away possible influence from other variables. This highlights how the household characteristics, with their rather low correlations to the user behaviour parameters like $PROFILE_{WEEK}$ and TSETBACK (see correlation matrix 3.18), are only of minor importance for the final energy use for space heating.

Table 5.2: Regression coefficients following the model of Equation 5.5, both for the poorly insulated dwelling 1 and the well insulated dwelling 7.
(-) coefficient not significantly different from zero at the α=0.01-level; (*) 0.001 < p-value ≤ 0.01; (**) p-value ≤ 0.001

	Dwelling 1 U_m = 1.24	*Dwelling 7* U_m = 0.27
INTERCEPT C	10.55**	8.52**
CATEGORICAL VARIABLES $\alpha_{j,c}$		
$PROFILE_{WEEK}$ | 1		
| 2	-	-
| 3	-	-0.09**
| 4	0.02*	-
| 5	-	-0.15**
| 6	0.02**	-0.20**
| 7	0.04**	-0.26**
$PROFILE_{WEEKEND}$ | 1		
| 2	-	-
| 3	-	-0.03*
| 4	0.02*	-
| 5	-	-0.04**
| 6	0.01*	-0.05**
| 7	0.01*	-0.09**
WHENSETBACK | 1		
| 2	-0.07**	-0.06**
| 3	-0.13**	-0.12**
| 4 & 5	-0.24**	-0.22**
PATTERNNIGHT | 1		
| 2	-0.19**	-0.25**
| 3	-0.31**	-0.30**
NUMERICAL VARIABLES $\hat{\beta}_i$		
TSETPOINT	1.21**	2.88**
TSETBACK	0.39**	0.07**
$QGAIN_{DAY,HIGH}$	-0.03*	-0.23**
$QGAIN_{DAY,INTERMED}$	-0.03**	-0.23**
$n_{WINDOWOPENING}$	0.04**	0.29**
ORIENTATION	-0.07**	-0.34**
$DEPTH_{EXTENSION}$	-	-
$DINS_{WALL}$	-0.08**	-0.22**
$DINS_{ROOF}$	-0.07**	-
$DINS_{FLOOR}$	-0.02**	-
N50	0.27**	0.10**
NVENT		0.16**
$EFF_{VENT,RECOVERY}$		-0.37**
$EFF_{HEAT,TOTAL}$	-1.00**	-1.03**
$\mathbf{R^2}$	**0.91**	**0.89**

Analysis of the categorical input parameters

A regression coefficient of $\alpha_{j,c=3}$ = -0.31/-0.30 for category 3 of variable PATTERNNIGHT means that changing from category 1 (heating the nightzone identically to the dayzone) to category 3 (never heating the nightzone) leads to a drop in total energy use of about 30 % for both dwellings. Or, the influence of PATTERNNIGHT as already detected in the preliminary analysis of the previous section is quantified here. A similar order of magnitude is estimated for the categories of WHENSETBACK, depicting how both variables are important items in the behavioural model, whatever the insulation quality of the dwelling.

The influence of the occupancy profile is more dwelling dependent. For the well insulated dwelling, being at home during more hours (the higher categories of $\text{PROFILE}_{WEEK/WEEKEND}$) results in lower energy uses (-0.26) due to the longer periods of internal heat gains dissipation. For the poorly insulated dwelling this effect is counterbalanced by the longer heating demand periods, resulting in slightly higher energy uses (+0.04). This will be further elaborated in the analysis of the Spearman's rank correlation coefficients.

Analysis of the numerical input parameters

The highest coefficients $\hat{\beta}_i$ are found for the setpoint temperature TSETPOINT: +1.21 and +2.88 for the poorly and the well insulated dwelling respectively, implying that a change in mean set-point temperature by 1 % results in a respective increase of total energy use by 1.21 % and 2.88 %. Or, when a dwelling is very well insulated, the energy use is more than twice as sensitive to the dayzone set temperature than for a poorly insulated dwelling. The same coefficient interpretation is applicable to the normalized sensitivity coefficients in the local sensitivity analysis of Firth et al. (2010), where a value of +1.55 was calculated for the heating demand temperature, weighted averaged over 47 house archetypes. Values of +1.55 and +1.15 were found by Cheng and Steemers (2011) and Kavgic et al. (2013) respectively when applying that same method on their building stock models. Given that, until nowadays, the main building stock characteristics are much alike those of poorly and moderately insulated dwellings, a reasonable accordance is found between the TSETPOINT-value for the poorly insulated dwelling in this work (+1.21) and the values found in the literature. Also, in all three studies the coefficient of the heating demand temperature was by far the highest ones, similarly as in this work. Concerning the setback temperature TSETBACK no comparison can be made with the literature values because typically this parameter is not included. Through this analysis though it is demonstrated how the setback temperature is quite important for a poorly insulated dwelling (+0.39), yet barely important (+0.07) when the thermal quality is sufficiently high (certainly in combination with the high thermal mass of the brick and concrete structures from the case dwellings).

It is clear how also the heating system efficiency proves to be a very sensitive parameter for both dwellings (-1.00/-1.03). Compared with the equivalent value of -0.60 found in Kavgic et al. (2013) (for mean heating system efficiency of 0.71) the here generated values are quite high. As Firth et al. (2010) and Cheng and Steemers (2011) only considered the boiler efficiency, they consequently found even lower values (-0.45 and -0.48 respectively), impeding a proper comparison.

Due to the nature of the coefficients $\hat{\beta}_i$ they can be ordered from high to low sensitivity, leading to Table 5.3. Overall though, it must be kept in mind that the coefficients $\hat{\beta}_i$ estimate relative effects on the output. For example, increasing the wall insulation thickness by 1cm, leads to an energy decrease of $(100 \times \beta_i) \times$ 1cm= $100 \times \hat{\beta}_i/\mu_{WALL,d} \times$ 1cm = $100 \times$ (-0.08)/2cm $\times$ 1cm = 4 % of total energy use for the poorly insulated dwelling, corresponding to 1227 kWh. Increasing the insulation thickness of the well insulated dwelling by that same 1 cm, leads to an energy use decrease of $100 \times$ (-0.22)/15cm $\times$ 1cm = 1.46 %, a lower percentage than the poorly insulated dwelling and corresponding to only 50 kWh. Certainly when translated into heating costs, it is obvious how 1 cm extra wall insulation is much more beneficial for the poorly insulated dwelling - despite the fact that its relative sensitivity indicator $\hat{\beta}_i$ is lower than for the well insulated dwelling. This highlights how comparing normalised sensitivity indicators like $\hat{\beta}_i$ must be carefully done when the input distributions and resulting mean values are different. Therefore, the input parameters with different input distributions are indicated in Table 5.3.

Table 5.3: Ranking of the numerical input parameters, based on the coefficients $\hat{\beta}_i$ of Table 5.2 (only if significant at the α = 0.01 level).
($^\bullet$) = different input distributions for both dwellings - see Table 5.1

RANK	*Dwelling 1* U_m = 1.24 W/(m^{2}K)		*Dwelling 7* U_m = 0.27 W/(m^{2}K)	
1	TSETPOINT	1.21	TSETPOINT	2.88
2	$EFF_{HEAT,TOTAL}$	-1.00	$EFF_{HEAT,TOTAL}$	-1.03
3	TSETBACK	0.39	$EFF_{VENT,RECOVERY}$	-0.37$^\bullet$
4	N50	0.27$^\bullet$	ORIENTATION	-0.34
5	$DINS_{WALL}$	-0.08$^\bullet$	$n_{WINDOWOPENING}$	0.29
6	ORIENTATION	-0.07	$QGAIN_{DAY,HIGH}$	-0.23
7	$DINS_{ROOF}$	-0.07$^\bullet$	$QGAIN_{DAY,INTERMED}$	-0.23
8	$n_{WINDOWOPENING}$	0.04	$DINS_{WALL}$	-0.22$^\bullet$
9	$QGAIN_{DAY,HIGH}$	-0.03	NVENT	0.16$^\bullet$
10	$QGAIN_{DAY,INTERMED}$	-0.03	N50	0.10$^\bullet$
11	$DINS_{FLOOR}$	-0.02$^\bullet$	TSETBACK	0.07

For the poorly insulated dwelling, apart from the setpoint and setback temperature, the heating efficiency and the air permeability n_{50}, the energy use is remarkably less sensitive to the other (numerical) building or behavioural parameters like the internal heat gains, orientation and floor insulation thickness. Still though, as illustrated above for DINSWALL, even these limitedly influential parameters can have a significant impact in absolute units.

For the well insulated dwelling the setpoint temperature and heating efficiency are also clearly predominant, but now the difference with all other sensitivity coefficients is less pronounced. This indicates how the energy use of these kind of dwellings is influenced by many more input parameters. For example, the well insulated dwelling is more sensitive to the internal heat gains (-0.23/-0.23 for $QGAIN_{DAY,HIGH}$ and $QGAIN_{DAY,INTERMED}$ respectively) than the poorly insulated one (-0.03/-0.03). While the latter is on his turn rather sensitive to the infiltration rate (N50 +0.27) and barely to the window opening (+0.04), the opposite is true for the well insulated dwelling (N50 +0.10, $n_{WINDOWOPENING}$ +0.29 and also NVENT +0.16). It confirms that the heat losses through air flows, whether through (uncontrolled) infiltration, window opening or hygienic ventilation, remain important in the total energy use of both dwellings.

The multiple linear regression is used here to enable comparison between the behavioural model and (a restricted amount of) building parameters. The results now show how the energy use for space heating is comparably sensitive to user behaviour parameters as it is for building parameters. The two most important variables are both a behavioural one (TSETPOINT) and building-related one ($EFF_{HEAT,TOTAL}$) and also in the following lower rankings no clear hierarchy is detectable. So, based on the above sensitivity analysis, correctly estimating building parameters is equally important as correctly estimating user behaviour actions. Of course, the final effect on the energy use is still highly dependent on the degree of input variability for each of the parameters. For example, despite the rather weak sensitivity to the ventilation air change rate NVENT (+0.16) in the well insulated dwelling, the overall importance of NVENT in the energy use could turn out to be quite substantial due to the large uncertainty around its mean value (see boxplot in Figure 4.6b).

5.3.4 Uncertainty analysis: Spearman's rank correlation coefficients

With the input variability of the behavioural parameters fairly well-known their contribution to the output variability can be assessed by computing Spearman's rank correlation coefficients. As said, these coefficients are input distribution dependent, in contrast with the previous regression coefficients. Also they equally apply on categorical variables, enabling a direct comparison with the numerical variables in terms of share in the output variability.

Datasets are generated by sampling p = 13 behavioural parameters in n = 3000 runs. These are the same datasets as generated in 5.2. Again, the same sampling scheme is used for both dwellings. By doing so, an artificial energy saving distribution can be constructed −without the need for extra simulations− by taking the difference between both output values. The 3000 so obtained values thus reflect the change in energy use when the original, poorly insulated dwelling is to be renovated to a very well insulated dwelling, thereby keeping the same variation in user behaviour. The latter means that no adaptive behaviour like the rebound effect is thus taken into account, in which users behave differently after renovation due to the lower energy costs. Interestingly though, also an uncertainty analysis on the energy savings can be performed.

Scatterplots

Based on the recommendations of Janssen et al. (2013) the correlation coefficients are complemented with scatterplots between all input parameters and the output. The latter are shown first in Figure 5.8. The scatterplots of the energy savings are not shown, since they are very similar to the scatterplots of dwelling 1. The energy uses at the Y-axis are scaled following $Y_{i,scaled}$ = (Y_i - Y_{min})/(Y_{min} - Y_{max}), allowing easy comparison between both dwellings and visualizing the stronger skewness of the energy use in the well insulated dwelling.

Visually checking scatterplots is useful here to detect tendencies in the data that cannot be investigated through a numerical analysis. For example, the scatterplot of NUMOCC has a clear triangle shape, depicting how the larger households are never associated with large energy uses due to the higher internal heat gains. Despite this being a clear tendency, it is not one that can be

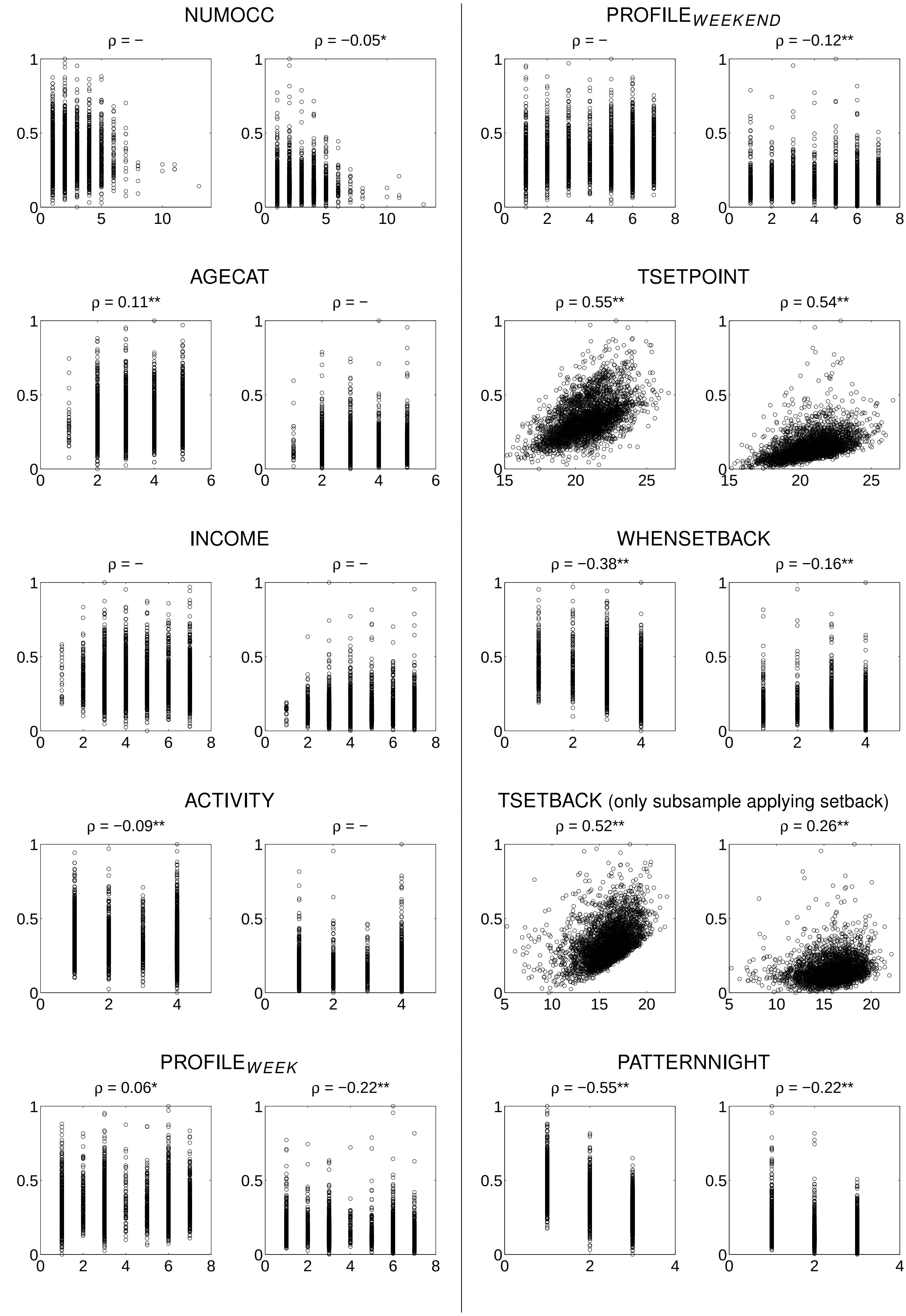


Figure 5.8: Scatterplots between each of the behavioural parameters and the total energy use for space heating, scaled between the minimum and maximum occurring value (left of 2 plots = dwelling 1; right = dwelling 7). For the explanation of the x-labels : see Table 3.15 and 3.17.
ρ = Spearman's rank correlation coefficient; (–) ρ not significantly different from zero at the α=0.01-level; (*) 0.001 < p-value ≤ 0.01; (**) p-value ≤ 0.001

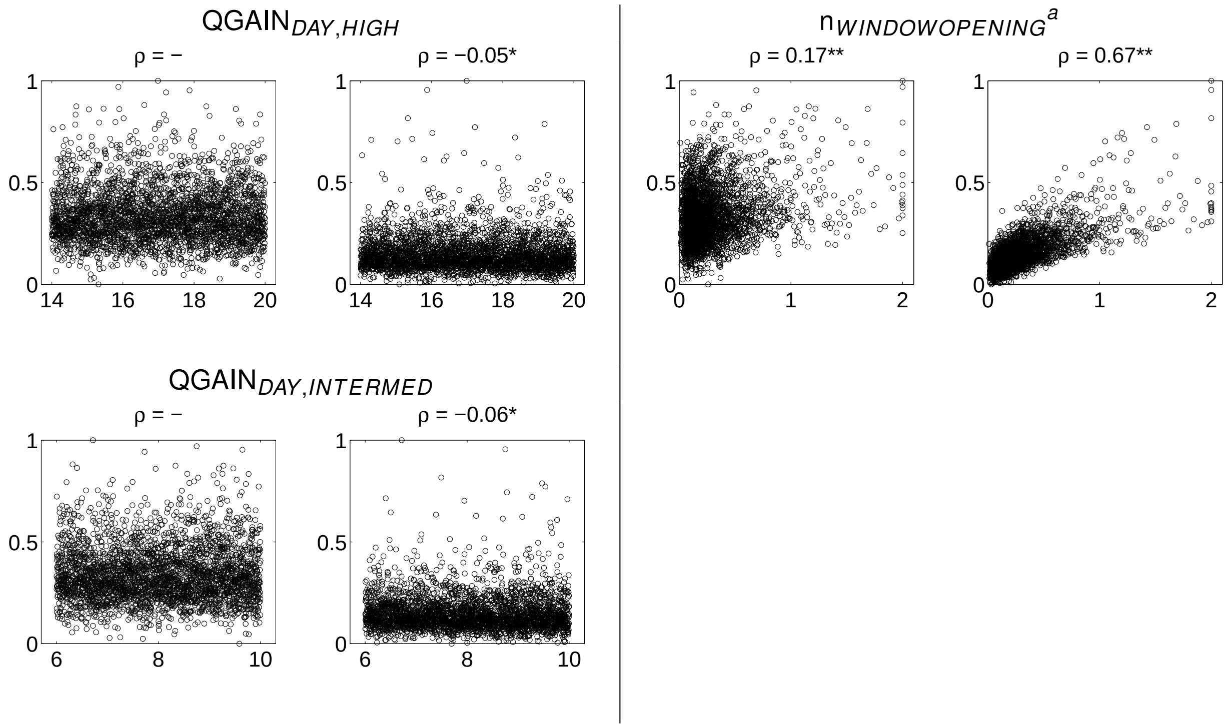


Figure 5.9: Continuation of Figure 5.8.

[a]$n_{WINDOWOPENING}$:The gathering of points at 2 h^{-1} is due to the cut-off of the logarithmic distribution at that value (see 4.4.1) to avoid unrealistically high window opening air change rates.

discovered via the correlation coefficient (only monotonically in- or decreasing tendencies can be detected).

Spearman's rank correlation coefficients

In Table 5.4 the Spearman's rank correlation coefficients with the total energy use for space heating and the energy savings are given for each of the input parameters.

It is immediately clear how all four heating preferences TSETPOINT, TSETBACK, WHENSETBACK and PATTERNNIGHT take up the largest share in the energy use variability of the poorly insulated dwelling: their correlation coefficients are significantly higher than those of the household characteristics, occupancy profiles or window opening behaviour. Whereas the three first heating preferences are quite well-known and documented, the opposite is true for PATTERNNIGHT. Severe assumptions had to be made concerning the heating behaviour in the nightzone, turning PATTERNNIGHT into a critical parameter of the behavioural model. Due to the fact that the household characteristics are correlated with TSETPOINT, TSETBACK and WHENSETBACK −in the sense that older people, lower incomes and lower activity levels tend towards less economic heating behaviour (see Table 3.18)− it is no surprise that their (small) correlation coefficients with the energy use are similarly interpretable. The internal heat gains prove to be of no importance for the final energy use variability in a poorly insulated dwelling.

For the well insulated dwelling the four heating preferences remain important contributors, though to a lesser extent, explaining why now the influence of the household characteristics is not visible

Table 5.4: Spearman's rank correlation coefficients between the total energy use for space heating and each of the behavioural parameters .
(–) ρ not significantly different from zero at the α=0.01-level; (*) 0.001 < p-value ≤ 0.01; (**) p-value ≤ 0.001

	Dwelling 1 U_m = 1.24 W/(m²K) $E_{tot,use,1}$	Dwelling 7 U_m = 0.27 W/(m²K) $E_{tot,use,7}$	E_{saving} = $E_{tot,use,1}$ - $E_{tot,use,7}$
NUMOCC	-0.05*	-0.11**	-
AGECAT	0.14**	-	0.15**
INCOME	-	-	-0.05*
ACTIVITY	-0.15**	-	-0.16**
$PROFILE_{WEEK}$	0.05*	-0.25**	0.12**
$PROFILE_{WEEKEND}$	-	-0.11**	0.05*
TSETPOINT	0.53**	0.54**	0.48**
WHENSETBACK	-0.38**	-0.16**	-0.41**
TSETBACK	0.49**	0.21**	0.51**
PATTERNNIGHT	-0.55**	-0.21**	-0.58**
$QGAIN_{DAY,HIGH}$	-	-0.07**	-
$QGAIN_{DAY,INTERMED}$	-	-0.07**	-
$n_{WINDOWOPENING}$	0.14**	0.66**	-

anymore. The internal heat gains and occupancy profiles have clearly gained in importance and especially the high correlation coefficient for the window opening behaviour is remarkable. Despite the energy use being only moderately sensitive to $n_{WINDOWOPENING}$ (see Table 5.3), the adopted spread in $n_{WINDOWOPENING}$ is that large that window opening behaviour eventually turns into a highly dominant parameter. However, this finding must be put in perspective. First, it was shown how the values for $n_{WINDOWOPENING}$, based on measured air change rates in fairly airtight Danish dwellings, possibly form an overestimation of actual air change rates (see 4.4.1). Second, in well insulated dwellings, equipped with a balanced ventilation system with heat recovery, the window opening behaviour, if any, might be much more limited than in dwellings without any ventilation system. Hence in reality, the influence of $n_{WINDOWOPENING}$ is likely to be considerably smaller. The finding does highlight how the window opening air change rates need extra research, not only in their absolute values but also in their correlation with installed ventilation systems.

By means of illustration the variability $n_{WINDOWOPENING}$ is reduced by only looking at the subgroup of users (1047 out of 3000) who adopt window air change rates lower than 0.15 h^{-1}. The correlation coefficients are shown in Table 5.5. For the poorly insulated dwelling the window opening behaviour now disappears as contributing parameter with the other coefficients being rather unaffected. For the well insulated dwelling all parameters significantly gain in importance at the expense of $n_{WINDOWOPENING}$ –which still remains fairly important in the output–, illustrating how the large variability of the latter overshadowed the other input variabilities.

When looking at the correlation coefficients of the energy savings, it is visible how almost all coefficients are very similar to the ones from the energy use before renovation. Though as expected, it does confirm how predicting reliable energy savings is more a question of estimating the initial energy use correctly than predicting the new, much lower energy use correctly. Yet, not all renovations are as extreme as is the case here (the energy use is expected to drop with a factor 6 after

Table 5.5: Spearman's rank correlation coefficients for the subgroup: $n_{WINDOWOPENING} < 0.15\ h^{-1}$ (n = 1047). (−) ρ not significantly different from zero at the α=0.01-level; (*) 0.001 < p-value ≤ 0.01; (**) p-value ≤ 0.001

	Dwelling 1 $U_m = 1.24\ W/(m^2K)$ $E_{tot,use,1}$	*Dwelling 7* $U_m = 0.27\ W/(m^2K)$ $E_{tot,use,7}$	$E_{saving} = E_{tot,use,1} - E_{tot,use,7}$
NUMOCC	-	-0.16**	-
AGECAT	0.17**	-	0.19**
INCOME	-	-	-0.08*
ACTIVITY	-0.18**	-	-0.20**
$PROFILE_{WEEK}$	-	-0.34**	0.14**
$PROFILE_{WEEKEND}$	-	-0.18**	-
TSETPOINT	0.57**	0.80**	0.51**
WHENSETBACK	-0.41**	-0.18**	-0.42**
TSETBACK	0.54**	0.35**	0.54**
PATTERNNIGHT	-0.53**	-0.15**	-0.56**
$QGAIN_{DAY,HIGH}$	-	-	-
$QGAIN_{DAY,INTERMED}$	-	-0.10*	-
$n_{WINDOWOPENING}$	-	0.23**	-

renovation), so this finding is probably less pronounced with more moderate renovation measures.

One final note must be made about the influence of the occupancy profiles on the energy use for space heating. For the well insulated dwelling, being at home and awake during more hours a day leads to a reduction of energy use (-0.25 and -0.11 for week and weekend profile respectively), indicating that the longer periods of internal heat gains dissipation overrule the longer heat demand periods. Rather surprisingly though, the profiles seem to be of limited importance in the poorly insulated dwelling (only +0.05 for $PROFILE_{WEEK}$ and not significant (-) for $PROFILE_{WEEKEND}$). This is due to the fact that the correlation coefficients apply for the total sample, which also contains the users who never or only rarely apply setback (see Figure 3.7). For the latter users, the occupancy profile is no or only a very poor indicator of daily heating hours and is only relevant in assessing when internal heat gains are dissipated. As the internal heat gains are of negligible importance for the energy use of a poorly insulated dwelling (see above), so is then the occupancy profile. For the large group of users who do apply setback however, the situation is different. When analysing the subgroup of users who apply setback whenever away or sleeping (WHENSETBACK = 4 and 5 , n = 1549), the correlation coefficients for $PROFILE_{WEEK}$ and $PROFILE_{WEEKEND}$ are now +0.20 and +0.09 respectively ($p \leq 0.001$), with all other parameters almost unaffected. So for this subgroup, when living in a poorly insulated dwelling, the degree of occupancy is indeed important for the energy use for space heating, though not as important as the heating preferences themselves (e.g. TSETPOINT remains high at +0.55).

5.3.5 Influence of different zoning patterns

Throughout this research work, only one zoning pattern is considered for the current case study: the dayzone at ground floor and the nightzone at first floor. By doing so, the real-life variation of inhabitants heating a greater or smaller spatial fraction of their dwellings is not fully captured by the behavioural model. The nightzone heating behaviour, with its 20 % of users heating the nightzone identically to the dayzone, does incorporate a single-zone pattern[2], but does not allow to get insight in the 'intermediate' spatial heating patterns. It is therefore investigated in this section how other zoning patterns, with more or less share of heated against unheated area, influence the output and sensitivities of the behavioural model.

Starting from the two above fictitious dwellings (see Table 5.1), 10 additional zoning patterns are constructed, ranging from low to high ratios of dayzone to total dwelling floor area. The patterns are shown in Table 5.6. In order to keep total calculation time reasonable, a space-filling LHS scheme

Table 5.6: Zoning variants: all rooms with 'x' are included in the dayzone. Floor plans: see Figure 4.9 page 116.

VARIANTS	original	1	2	3	4	5	6	7	8	9	10
Ground Floor											
living room	x	x[a]	x	x	x	x	x	x	x	x	x
kitchen	x			x	x	x	x	x	x	x	x
hallway	x			x	x	x	x	x	x	x	x
storage	x					x	x	x	x	x	x
garage	x						x	x	x	x	x
extension (depth 3 m)	x	x	x	x	x	x	x	x	x	x	x
First Floor											
bathroom					x	x	x	x	x	x	x
bedroom 1								x	x	x	x
bedroom 2									x	x	x
bedroom 3										x	x
office											x
hallway									x	x	x
$A_{floor,DAY}$ [m^2]	108	43	60	82	90	102	117	135	167	182	191
$A_{floor,DAY}/A_{floor,TOT}$ [-]	0.57	0.22	0.31	0.43	0.47	0.54	0.61	0.71	0.87	0.95	1.00

[a]For this variant only that half of the living room adjacent to the extension is included in the dayzone

of only 1500 users (and not the previous 3000) is generated and imposed, not only to all of these additional 2x10 dwellings, but also to the 2 dwellings with original zoning pattern in order to eliminate possible anomalies in the results due to the different sampling schemes (3000 against 1500).

It must be noted that throughout the following analysis, the remainder of both behavioural and building model are unaltered. This implies that, by altering the floor areas of both day- and nightzone, the total internal heat gains within the dwelling (expressed as a function of square meter floor area (see Table 3.13 on page 68)) will change automatically. Also, the convective losses due to window opening behaviour (only imposed to the nightzone by means of an air change rate per m^3 volume - see 4.4.1) will be reduced when moving towards smaller nightzones.

[2]These 20 % of users act very similar, yet do not coincide, with a 100 % dayzone modelling, because they only 'heat' but not 'use' their nightzone identically to the dayzone (internal heating gains still considerably lower, window opening behaviour in the nightzone)

Energy use for space heating

In Figure 5.10 the total energy use for space heating is plotted as a function of the ratio $A_{floor,DAY}$ $/A_{floor,TOT}$ [-].

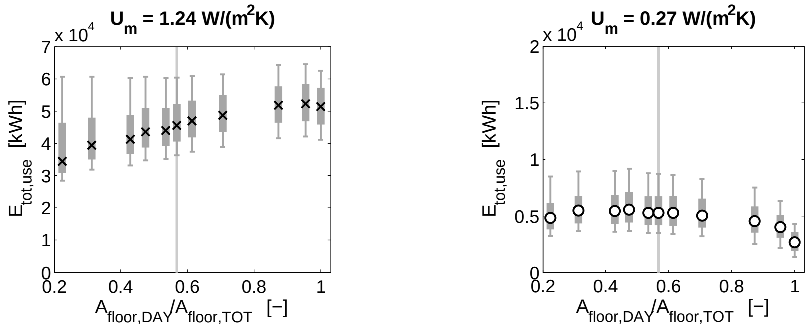


Figure 5.10: Total energy use for space heating $E_{tot,use}$ [kWh] as a function of $A_{floor,DAY}/A_{floor,TOT}$ [-], for the poorly (U_m = 1.24 W/(m^2K)) and the well (U_m = 0.27 W/(m^2K)) insulated dwelling.
Vertical line: original zoning pattern. Markers: median ; box: 25th until 75th percentile ; whiskers: 10th until 90th percentile.

When looking at the poorly insulated dwelling, the energy uses act as expected: the higher the dayzone ratio, the higher the energy use. When analysing the very well insulated dwelling, it must be kept in mind that the internal heat gains have much higher impact in the very well insulated dwelling. So, while for the very low dayzone ratios, the same increasing trend is observed, the opposite is seen as soon as $A_{floor,DAY}/A_{floor,TOT}$ reaches ± 0.4: the energy use drops because the higher internal heat gains of the dayzone overrule the higher heated area. For the poorly insulated dwelling, this effect is subordinate to the higher heated area and thus not visible (only for the small descent from variant 9 to 10, the internal heat gains might play a role; however, it might also be a coincidental sampling consequence).

In Figure 5.10 however, all users are considered, also those 20 % of users who heat their nightzone identically as the dayzone. Since these inhabitants 'interfere' with the zoning patterns, they are left out in Figure 5.11 to allow for a more straightforward insight in the influence of the zoning patterns. As expected, both the large spread and strong skewness of the errorbars at the low

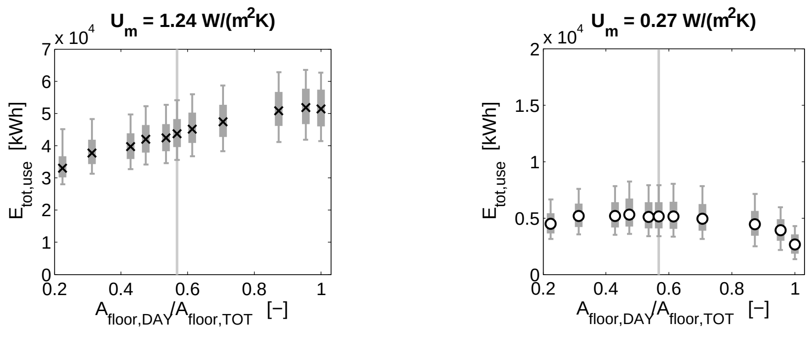


*Figure 5.11: Total energy use for space heating $E_{tot,use}$ [kWh] as a function of the ratio dayzone floor area against total dwelling floor area, for the poorly (U_m = 1.24 W/(m^2K)) and the well (U_m = 0.27 W/(m^2K)) insulated dwelling –**only those users who never heat the nightzone or only during the night (PATTERNNIGHT = 3 or 2)**.*

dayzone ratios are now significantly reduced, certainly for the poorly insulated dwelling. The median energy uses of the lowest and highest dayzone ratios are about 15 % lower, resp. higher, than the median energy use of the original zoning pattern, hence revealing the importance of a different zoning pattern on the energy use.

Spearman's rank correlation coefficient

In Figure 5.12 the Spearman's rank correlation coefficients are shown for the 6 most important behavioural parameters; note the different signs at the y-axis.

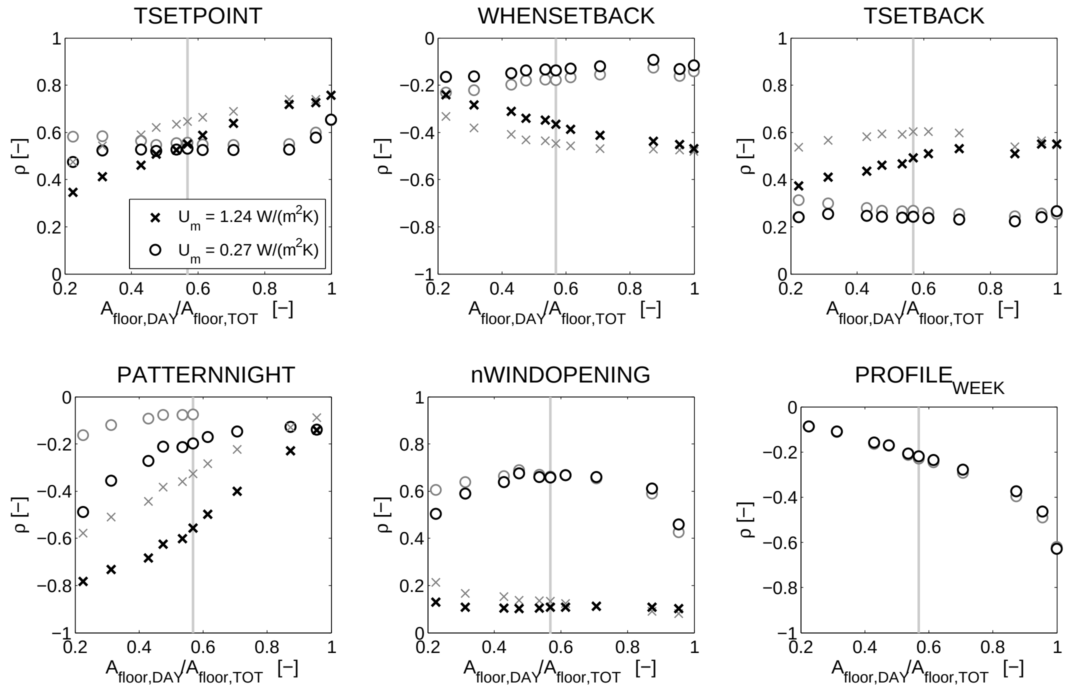


Figure 5.12: Influence of different zoning patterns on the Spearman's rank correlation coefficient ρ (only shown if statistically significant at the α = 0.001 level) between 6 behavioural parameters and the total energy use for space heating, for the poorly (U_m = 1.24 W/(m^2K)) and the well (U_m = 0.27 W/(m^2K)) insulated dwelling. In grey: only those users who never heat the nightzone or only during the night (PATTERNNIGHT = 3 or 2).

As expected, those parameters that predominantly determine the dayzone heating behaviour (TSETPOINT, WHENSETBACK, TSETBACK) have increasing impacts when the dayzone ratios increase, while those that determine the nightzone (PATTERNNIGHT) have decreasing impact. The reverse U-shape of the nightzone window opening behaviour (nWINDOPENING) in the well insulated dwelling is explained by the 'contact area' between day- and nightzone. For the zoning patterns chosen here, the highest contact area is reached for the intermediate dayzone ratios, the lowest contact areas for low and high dayzone ratios. It illustrates how the heat transfer between both zones, even if, like in this work, only conductive heat transfer is included, is fairly important in a well insulated dwelling.

Again, those who heat the nightzone identically to the dayzone are excluded; these results are shown in grey. Now the nightzone heating behaviour gets less important (its interpretation is now reduced to whether or not the nightzone is heated to TSETBACK during the night), yet remains important in the poorly insulated dwelling, while the temperature settings in the dayzone now gain in importance. In the very well insulated dwelling, however, all correlations with the behavioural parameters remain fairly unaltered, except from the nightzone behaviour, which becomes redundant: whether or not the nightzone is kept at setback temperature during the night, is now of no or negligible influence to the energy use.

Discussion

In the current behavioural model, spatial zoning is already quite rudimentary accounted for through the nightzone heating behaviour. When additional zoning patterns are investigated, the above results make clear that the sensitivities to the behavioural parameters change as a function of the varying heated space fraction, and this in a very logical way: the smaller the heated space fraction, the less influential the behaviour in the dayzone and the more influential the behaviour in the nightzone. In order to automatically incorporate these trends, the kind of zoning pattern could be included as a probabilistic input parameter in the behavioural model. Given a probability distribution of the percentage heated floor area, as for instance available in the ECS-database (see Figure 3.18 page 81), and given a predefined set of zoning patterns with respective dayzone ratios, a single zoning pattern can then be stochastically attributed to each of the users. When doing so however, the nightzone heating can no longer contain those 20 % of users heating day- and nightzone identically, because they cause an undesired interference between nightzone behaviour and spatial zoning (for instance, it makes no sense in combining a user with low dayzone ratio with a nightzone heating behaviour in which the nightzone is heated identical to the dayzone).

Also, the above analysis highlights how further refinements to the behavioural and building model should be considered if they are to be used for very well insulated dwellings. Not only because the internal heat gains are very important in these dwellings and thus need to be assessed more reliably than solely based on square meter floor area, but also because the rigid separation in day- and nightzone might become a redundant assumption. While it is valid in poorly insulated dwellings, in which inhabitants use and heat only part of their dwelling and consciously close internal doors to maintain the heat in the living rooms, it might no longer hold in an airtight, well insulated dwelling. More uniform temperatures are found throughout these houses, not only due to the different dwelling characteristics (better insulation quality, (pre-heating) ventilation system, high performing central heating system etc.), but also due to the inhabitants behaving differently: driven by the more uniform temperatures and/or lower energy costs, they might use/heat a larger share of their house and/or be less strict in closing internal doors (=rebound effect). Evidence is for instance found in the measurement campaign in low energy houses of Staepels et al. (2013), where living and bedroom temperatures were high and very similar, suggesting that a single zone approach (both in behavioural and building model) could be equally valid for these dwellings. Regarding the above analysis, this means that the actual sensitivities of a low energy house might be more situated at the high dayzone ratios (~single-zone approach) than at the intermediate dayzone ratio from the current behavioural model.

5.4 Comparison of methodology with measurements

The previous sensitivity and uncertainty analysis already built up knowledge about the developed methodology and mainly about the impact of the probabilistic behavioural model on the calculated energy use for space heating. However, it does not provide insight into how these calculated energy uses compare to real-life energy uses. Only if the accordance is fairly well, one can rely on the developed methodology to estimate reliable energy use, and thus, more reliable energy savings.

One should keep in mind that the developed framework of behavioural model in combination with the two-zone building model is intended to be used on an aggregated level, and not on the individual 'dwelling-with-particular-household' level. Therefore, any comparison of simulations with measurement data should be performed on a minimally aggregated level and not on the individual level. To do so, the case study with the 10 real Lijsterlaan dwellings is used here. A monitoring campaign has been set up in these dwellings, including indoor temperature measurements in both living and bedroom and the weekly logging of energy use. Comparing the complete set of these 10 dwellings with the overall model output gives a first indication of the global reliability of the model. In addition, the 21 fictitious Lijsterlaan variants are added and the model output is compared with large-scale Belgian measurement campaigns as found in the literature.

Although estimating reliable indoor temperatures is not the main target of the developed methodology, the modelled indoor temperatures do provide insight in how the behavioural model affects the indoor environment. Therefore, the indoor temperatures are investigated first. Afterwards, the energy use for space heating is discussed.

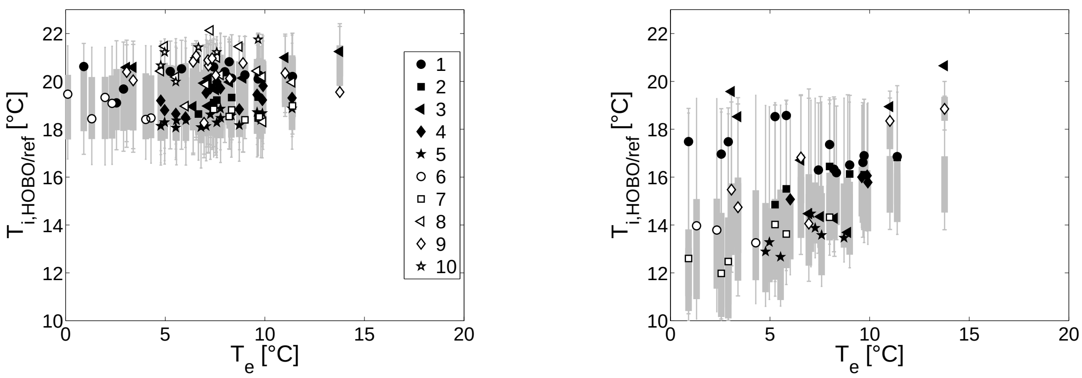
5.4.1 Indoor temperatures

10 actual Lijsterlaan dwellings: monitoring data

During the Belgian winter 2012-2013 the indoor temperatures have been monitored in the 10 real Lijsterlaan dwellings. HOBO data loggers have been placed in the main living room and main bedroom during a couple of days. As already mentioned in this work, the temperature measured by a HOBO logger is mainly but not only the air temperature, since it is also influenced by the radiant temperature of the surroundings. Therefore, the indoor temperatures as measured by the HOBO loggers will be compared with the reference indoor temperature of the simulations (Equation 3.4).

In order to obtain comparable simulations results, the simulations are performed under the outdoor climate conditions as measured during the monitoring campaign. This is done by implementing the measured hourly data of external air temperature, horizontal solar radiation and wind speed into the `TRNSYS`-environment. As concluded by the previous section, 200 runs are performed for each of the 10 actual Lijsterlaan dwellings to account for the probabilistic variation in occupant behaviour; all dwelling parameters have been defined in Table 4.4 and are kept constant within the 200 runs.

In Figure 5.13 the measured and simulated daily mean indoor temperatures are plotted against



(a) living room / dayzone *(b) bedroom / nightzone*

Figure 5.13: Measured and simulated daily mean indoor temperatures as a function of the daily mean outdoor air temperature for the 10 Lijsterlaan dwellings.
Markers: measured ; Boxplots: simulated (box: 25th until 75th percentile ; whiskers: 10th until 90th percentile)

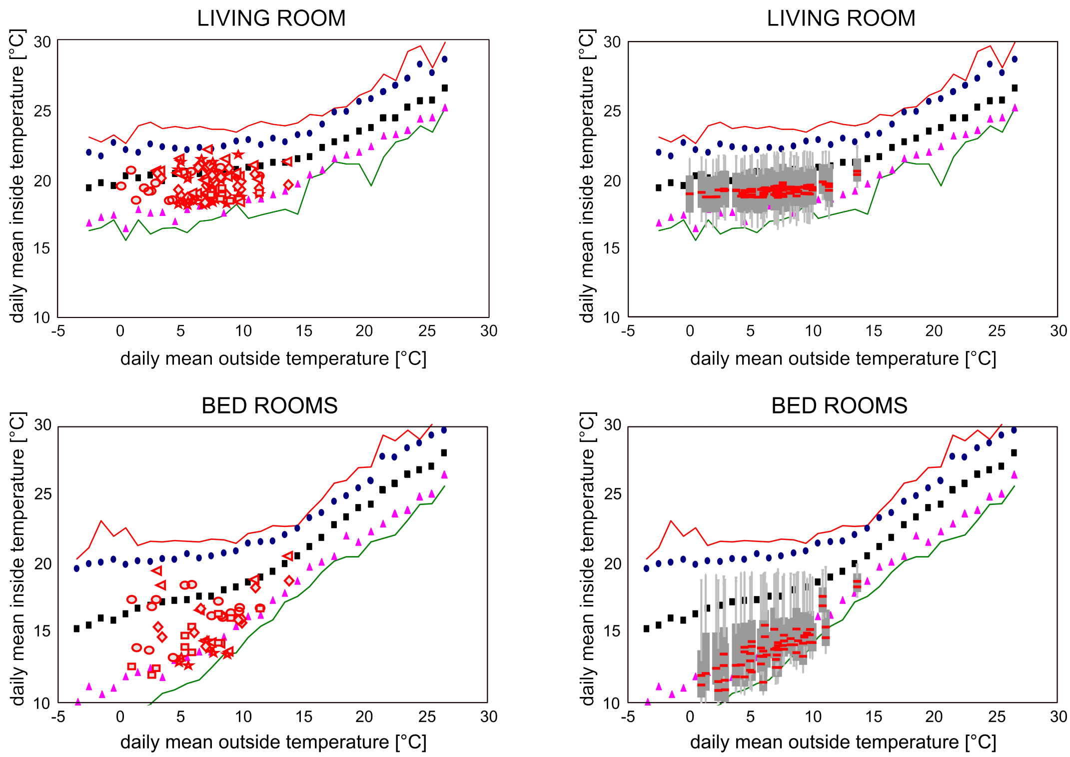
the daily mean outdoor air temperature. The whiskers of the simulated results incorporate 80 % of all values, depicting the huge range in possible indoor temperatures purely due to differences in user behaviour. Certainly for the nightzone temperatures, large variations are possible, mainly depending on which heating pattern is chosen −see preliminary analysis of section 5.2.

Overall, the simulated results seem to be in quite good correspondence with the measured results and capture well what is observed in real dwellings: the living room temperatures are almost independent of outside temperature, while the bedroom temperatures decrease in proportion to outside temperature. Furthermore, for the living room −where temperatures are predominantly driven by the heating behaviour− a satisfying agreement is found between measured and simulated data. For the bedroom the measured temperatures are more scattered, demonstrating how large variations are possible due to the mutual influence of (scarce) heating and building characteristics. This large variety is found equally well in the simulated temperatures.

Belgian measurement campaign, analysed by Janssens and Vandepitte (2006)

In a 2003-2005 Belgian measurement campaign[3] 39 dwellings have been selected across Belgium, in which the indoor climate is monitored every 10 minutes in different rooms during 6 months to 2 years. All dwellings (3 woodframe and 36 masonry houses) were detached and had a ventilation system installed. Approximately 65 % was built in the 1980's and 35 % built after 1990, so this sample is newer and probably somewhat better insulated than the Lijsterlaan sample. This is important knowledge, since the insulation level impacts how the indoor temperature of unheated rooms is correlated to the outdoor temperature. When the previous Lijsterlaan temperatures (both measured and simulated) are plotted on the graphs of Janssens and Vandepitte (2006), the graphs of Figure 5.14 are obtained.

[3] Measurement campaign was part of the project "Moisture problems in roofs: impact of the present boundary conditions and construction techniques in Belgium", carried out by the Belgian Building Research Institute (BBRI), University of Leuven (KU Leuven), Ghent University (UGent) and Hogeschool voor Wetenschap & Kunst (High School for Science & Art - W&K), and funded by the Belgian Government.



(a) Measured *(b) Simulated*[a]

[a]Marker = median ; box = 25th until 75th percentile ; line = 10th until 90th percentile

Figure 5.14: Daily mean indoor temperature as a function of the daily mean outdoor temperature: the 10 Lijsterlaan dwellings (red markers), compared with the measurement data found in Janssens and Vandepitte (2006).

The comparison with the Lijsterlaan measured temperatures (Figure 5.14a) is needed to demonstrate how the Lijsterlaan sample has rather low indoor temperatures compared to the Janssens sample, very likely due to the higher insulation levels of the latter. This must be kept in mind when interpreting the simulated temperatures of Figure 5.14b.

For the living room temperatures in Figure 5.14b a fairly good correspondence is found. Also for the bedroom temperatures, the overall slope and extent of the spread of the simulated points is very much alike those of the Janssens sample. However, while some measured values are indeed located under the 5th percentile of the Janssens sample (Figure 5.14a), a much more pronounced tendency is found in the simulated temperatures, where the median values almost coincide with that 5th percentile. Even though the Lijsterlaan and Janssens sample are very likely to have different insulation levels, thereby mainly impacting the bedroom temperatures, some additional reasons could be mentioned for these rather low simulated bedroom temperatures. First, as the temperature of a unheated space is predominantly determined by the outdoor conditions and by its own capacity to maintain incident gains, an inadequate modelling of physical processes like thermal capacity or solar incidence in TRNSYS is possible. Second, it is possible that the implemented window opening ventilation rates are too high. When the simulations are re-run with a window opening ventilation rate of 0 h^{-1} in all nightzones, all median nightzone temperatures are indeed about 1 °C higher

- the median energy uses are consequently about 5 % lower. Thirdly, an additional explanation is the underestimation of convective heat gains from the adjacent dayzone through the systematic opening of internal doors. In the building model, no such airflows are modelled, making both zones only exchanging heat by pure conduction. This is rather unlike reality, where internal doors are regularly opened and airflows can occur from the warm dayzone to the cold nightzone. Finally, it is possible that the behavioural model underestimates the actual heating behaviour in bedrooms and that households tend to heat the nightzone to a greater extent than assumed.

5.4.2 Energy use for space heating

Again, the computed energy use for space heating for the 10 real Lijsterlaan dwellings is first compared to the monitoring campaign. Afterwards the fictitious dwellings are added and the comparison is made with a Belgian measurement campaign.

10 real Lijsterlaan dwellings: monitoring data

Apart from the indoor temperatures, also the energy use has been monitored in the 10 real Lijsterlaan dwellings during the heating season 2012-2013. Unfortunately, the monitoring period is very short for some dwellings (only 7 days). Also, 9 of 10 dwellings rely on gas both for space heating and hot tapwater, so an estimation has to be made concerning the share of hot tapwater in the overall gas consumption, thereby inducing considerable uncertainty about the actual remaining measured energy use for space heating. To somewhat account for this, the energy use for hot tapwater is defined probabilistically first, consequently leading to a probabilistic estimation of the measured energy use for space heating.

The daily energy use for hot tapwater $E_{tap,d}$ is determined as:

$$E_{tap,d} = \frac{(\rho_w \dot{V}_{w,d}) \times c_w \times (T_{out} - T_{in})}{\eta_{overall,tap}} \qquad \text{[J/day]} \tag{5.6}$$

with ρ_w=1000 kg/m^3 the mass density of water, $\dot{V}_{w,d}$ the daily hot water consumption [m^3/day], c_w=4186 J/(kgK) the heat capacity of water, T_{out} and T_{in} the temperature of the outgoing hot, respectively incoming cold water [°C] and $\eta_{overall,tap}$ the total heating efficiency for the hot tap water preparation. T_{in} is kept fixed at 10 °C, being a reasonable estimate for winter conditions (EMC 2008). The 3 remaining parameters $\dot{V}_{w,d}$, T_{out} and $\eta_{overall,tap}$ are defined probabilistically as follows:

- The nominal value for $\dot{V}_{w,d}$ is derived from an extensive monitoring campaign on 120 UK houses (EMC 2008). Here, the total daily hot water consumption (at mean delivery temperature of 51.9 °C) has been derived as a function of the amount of occupants N as $\dot{V}_{w,d}$=40+28N [litres/day]. This value is in good accordance to Leefmilieu Brussel (2008), in which it is stated that "*the hot water consumption per household is in between 30 to 60 litres per day per person*". The amount of inhabitants N is known for every Lijsterlaan dwelling through the dwelling's survey. To account for the considerable scatter in the measurement data of EMC (2008), $\dot{V}_{w,d}$ is turned into a probabilistic parameter by adopting a uniform range of 50 % around this nominal value.

- The outgoing hot water temperature T_{out} is assumed to vary uniformly between [45 - 60] °C, a temperature range that was also observed in EMC (2008).
- The production efficiency for the hot tapwater generation is adopted from the Belgian energy performance calculation (EPR 2010) and equals 0.50 when the tapwater is immediately heated and 0.45 when a storage tank is used. To account for the distribution losses between boiler and each tap location, a distribution efficiency of 0.72 is adopted from EPR (2010). The nominal value $\eta_{overall,tap,nom}$ thus equals 0.36 when the tapwater is immediately heated and 0.32 when a storage tank is used. The overall efficiency $\eta_{overall,tap}$ is then assumed to vary uniformly within a range of [$\eta_{overall,tap,nom}$-0.05 ; $\eta_{overall,tap,nom}$+0.05].

10 000 runs of random sampling are used to generate the probabilistic estimation of daily hot tapwater use for every dwelling. After multiplication with the amount of days of the respective monitoring period and when extracting the latter values from the total measured energy consumption, the measured energy use for space heating is determined probabilistically.

In Figure 5.15 the median value of the measured energy use for space heating is plotted against the simulated one, together with the intervals from 10th until 90th percentile. The uncertainty in hot tapwater use (see horizontal width of errorbars) has only little effect on the overall picture. Also, it is clear how the duration of some monitoring periods has been too short to allow for a meaningful comparison (low energy uses in lower left corner). For the remaining points, large errors are possible on the individual level −illustrated by for example the median values above the 150 %-deviation line. Of course, the sample size is too small to draw a sound conclusion. It is encouraging though that there seems to be no clear trend in simulation error: the simulated energy use is sometimes higher and sometimes lower than measured. For the estimation of the energy use at the aggregated level it is important that individual errors are of symmetric/random nature.

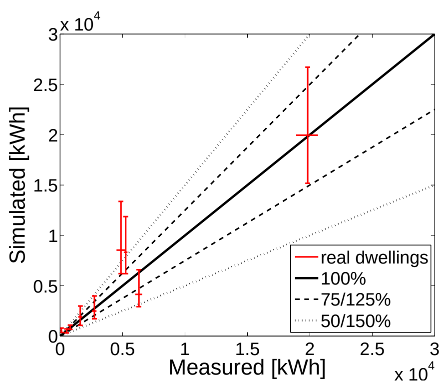


Figure 5.15: Simulated against measured energy use for space heating[a] for each Lijsterlaan dwelling and its respective survey period.

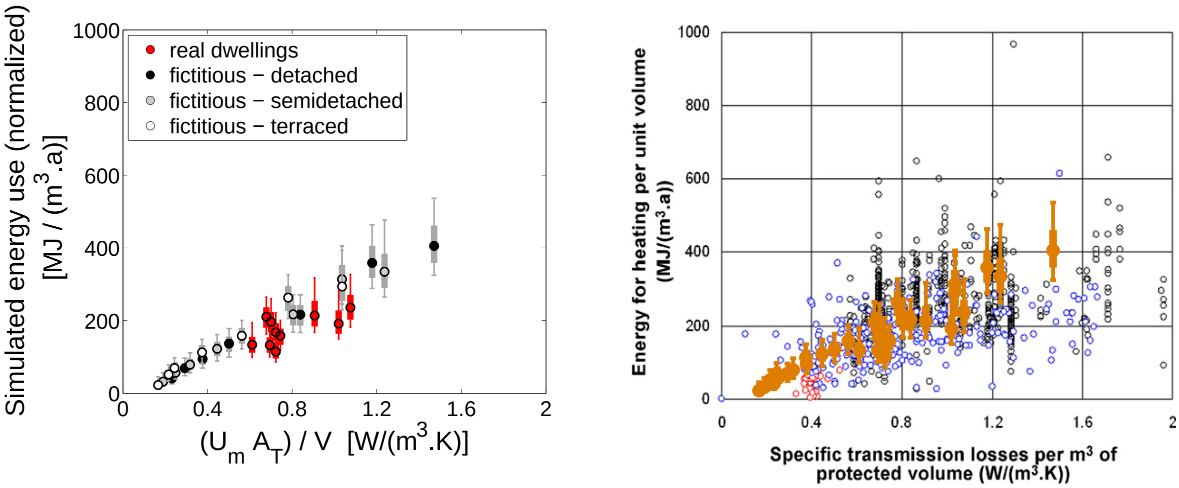
[a]crosspoint of errorbars = medians; vertical/horizontal errorbar = 10th until 90th percentile

Obviously, the sample size of these 10 dwellings is too small for any founded conclusion. Therefore, an additional comparison is made with measurement data from a large-scale measurement campaign on Belgian dwellings.

Belgian measurement data of Hens et al. (2010)

964 Belgian dwellings have been monitored between 2000 and 2005, of which 268 randomly chosen single family houses of all ages, 41 energy-efficient dwellings and 655 social houses (built between 1960 and 1999)(Hens et al. 2010, Hens 2006). All measured end energy uses for space heating have been normalized by the heating degree method to an outdoor weather year with 2087 heating degree days 15/15[4].

Concerning the simulations, the 10 real Lijsterlaan dwellings are now extended with the 21 fictitious Lijsterlaan dwellings. All 31 dwellings are now run under the METEONORM climate file of Ukkel, Belgium, with 2172 heating degree days 15/15. The annual energy uses for space heating are then normalized to the climate year of the measurement data by multiplication with a factor 2087/2172=0.96. The result is summarized in Figure 5.16 with the annual energy uses for space heating per unit of protected volume (V) expressed as a function of the specific transmission losses per unit of protected volume ($U_m A_T / V$).



(a) Simulated results only[a]

(b) Simulated results[a] *(in orange) projected onto Hens et al. (2010).*

[a]Marker = median ; box = 25th until 75th percentile ; whiskers = 10th until 90th percentile

Figure 5.16: The energy use for space heating per year per unit volume [MJ/(m^3.a)]: (a) simulated results and (b) compared to measurement data as found in Hens et al. (2010).

When looking at the separate simulation results (Figure 5.16a) it can be seen how, for similar values of $U_m A_T / V$, lower energy uses are found for the real dwellings compared to the fictitious dwellings. This is partly explained by the n_{50}-values adopted for the fictitious dwellings (see Table 4.5): these are rather high compared to the real dwellings and their effect is not incorporated in the

[4]A heating degree day 15/15 is defined as the difference between the daily outdoor temperature and 15 °C –if the outdoor temperature is higher than 15 °C, the heating degree day for that particular day equals zero.

heat transmission figure $U_m A_T/V$. In addition it is explained by the uneven spread of the insulation throughout the actual dwellings: the dayzones of the real dwellings –with their recent and insulated extensions– are globally better insulated than the nightzones (see Table 4.4). So, with the dayzone being more intensively heated than the nightzone, it is logical how this uneven spread of the insulation, even though it overall leads to a similar $U_m A_T/V$ value, is beneficial for the energy use for space heating. This will be further elaborated in 5.5.

Regarding the comparison with the measured data (Figure 5.16b) a good accordance is found, certainly in the range of $U_m A_T/V$ = [0.4 - 1.2]. The boxplots nicely cover the scatter cloud and the overall slope of the simulated results is very similar to the one of the measured data. For very well insulated dwellings ($U_m A_T/V$ < 0.4) it is difficult to draw any conclusions since only few measurement points are available. For the poorly insulated dwellings ($U_m A_T/V$ > 1.2) only a few simulation points are available, again impeding a robust conclusion. Nonetheless, the accordance with the measured values appears somewhat less good for these poorly insulated dwellings: the simulated results are at the higher end of the actual energy use. Part of it could be explained by the rather high air permeabilities used for the poorly insulated fictitious dwellings (see above). Yet, it is possibly also an indication that the behavioural model, although covering a wide range of different thermostat settings, overestimates the actual settings in very poorly insulated dwellings and/or that the heated area is overestimated.

5.5 Comparison of methodology with Belgian energy performance assessment calculation

In Chapter 2 the inappropriate use of energy labelling tools as predictive method has been identified as an important factor in shortfall. These tools systematically overestimate pre-retrofit use, thereby inevitably leading to shortfall when calculating energy savings. The question is whether this methodology is indeed able to do better. This is investigated in this section.

The calculation method of the Belgian energy performance assessment regulation is considered here, as it is commonly used in Belgium and forms a typical example of how an energy labelling tool is applied as predictive tool. Firstly, the main characteristics of the Belgian energy performance assessment calculation, called 'EPR method', are described. Secondly, it is investigated to what extent the heating season energy use for space heating of this EPR method deviates from the energy use as simulated by the here developed methodology, called 'detailed method'. Thirdly, a similar investigation is performed concerning the energy savings.

5.5.1 The Belgian energy performance calculation

The Belgian energy performance calculation (EPR 2010) is a quasi-steady state, monthly calculation method, largely based on the monthly method of ISO/FDIS 13790 (2008) and estimating, amongst others, an annual characteristic end energy use for space heating. The main characteristics (and the main areas of deviation with the here developed methodology) have already been mentioned throughout this dissertation and are summarized here:

- User behaviour is assessed in a simplified way:
  - The whole dwelling is considered as one single zone, constantly held at 18 °C.
  - Internal heat gains are constant in time and are formulated as a function of the dwelling volume V_i (see also Equation 3.6):

$$Q_{int,gain} = (0.67 + 220/V_i) \times V_i \qquad [\mathrm{W}] \tag{5.7}$$

  - Window opening behaviour is not taken into account.
- Air flows are calculated as follows:
  - The resulting air flows through in- and exfiltration are taken equal to

$$\dot{V}_{inf} = v_{inf,EPR} \times A_T = (0.04 \times v_{50}) \times A_T \qquad [\mathrm{m^3/h}] \tag{5.8}$$

    with v_{inf} and v_{50} [m^3/(m^{2}h)] the air infiltration rate respectively at normal conditions and at 50 Pa pressure difference, per square meter envelope area A_T [m^2]. In case no pressurization test has been performed, a v_{50}-value of 12 m^3/(m^{2}h) is to be adopted by default, corresponding to a rather high air permeability of $n_{50} = (v_{50} \times A_T)/V_i = 9.6$ h^{-1} for the Lijsterlaan geometry. This default value is not used for the current comparison. Instead the values as measured and assumed are taken over (see Table 4.4 and 4.5). Interestingly, the above equation implies a scaling value of $v_{inf}/v_{50} = 0.04$, which is lower than the equivalent scaling value $n_{inf}/n_{50} = 0.055$-0.056 obtained in the here developed building model when following the LBNL-method (see section 4.4.1).
  - Ventilation air flows are formulated as (see also Equation 4.10):

$$\dot{V}_{vent} = n_{vent,EPR} \cdot V_i = (m \cdot (0.2 + 0.5\exp(-V_i/500))) \cdot V_i \qquad [\mathrm{m^3/h}] \tag{5.9}$$

    with $m = 1.5$ by default, independently of the presence and characteristics of any ventilation system. If proof can be given that the ventilation system performs better than default (for details see EPR (2010)), m can be decreased to 1.26 for system A and 1 for system C and D. In the current comparison the latter m-values are adopted for the respective ventilation systems, while, in the absence of any ventilation system, the default value of $m = 1.5$ is taken over. When a heat recovery unit is installed, an efficiency of $\eta_{recov} = 0.70$ is assigned.
- The energy use for space heating is calculated on a monthly basis and formulated as (see also Equation 4.14):

$$E_{tot,use} = \frac{E_{net,demand}}{\eta_{overall,heat}} \qquad [\mathrm{kWh}] \tag{5.10}$$

with:

- $\eta_{overall,heat}$ the overall heating system efficiency, taken constant throughout the year. For hydronic heating systems with radiators and central room thermostat, the default efficiencies equal 0.74 in the case of a condensing boiler and 0.65 for a non-condensing boiler. By using a constant value for $\eta_{overall,heat}$, independently of the heat balance ratio (gains over losses) and hence independently of the insulation level of the dwelling, the drop in overall heating system efficiency, occurring when a poorly insulated house is renovated into a well insulated one whilst keeping the heating system, cannot be taken into account −in contrast to the detailed method which relies on the performance curves of Peeters et al. (2008) (Figure 4.8).
- $E_{net,demand,m}$ the net energy demand calculated as

$$E_{net,demand,m} = E_{losses,m} - \eta_{util,m} \times E_{gains,m} \qquad \text{[kWh]} \tag{5.11}$$

  with $E_{losses,m}$ the monthly transmission, ventilation and ex/infiltration losses and $E_{gains,m}$ the monthly internal and solar heat gains. $\eta_{util,m}$ is the monthly utilization factor, formulated as a function of the ratio $E_{gains,m}/E_{losses,m}$ and the thermal capacity of the dwelling (EPR 2010).

A freely available software '*EPB Software Vlaanderen version 1.8.4*' (Decysis 2013) is available to generate the end energy uses for space heating. This is not used here as it is provided as a 'black-box' tool, requiring a large amount of manual input handling per dwelling and allowing no internal adaptations like for instance changing the outdoor conditions. Instead, the scripts from Boonen and Moyaert (2014) are used, who implemented the EPR calculation methodology in MATLAB. Their scripts are validated within this work by implementing the 7 fictitious dwellings in open typology both in the MATLAB-scripts and in the EPB Software: both outcomes only differed by 0.5 %. To obtain the same outdoor conditions of the detailed method, the monthly external air temperature and monthly total and diffuse solar radiations are extracted from the Meteonorm-file used in TRNSYS and transferred to the MATLAB-scripts. From here on, all results from the EPR method are generated by means of this Meteonorm-climate (and not to the climate foreseen in the actual EPR methodology).

Any difference observed between the detailed method and the EPR method in the following subsection is of course not solely due to the different assessment of the aspects listed above (user behaviour, convective air flows, overall heating system efficiency and use of utilization factor to capture dynamic effects). A variety of additional (modelling) reasons are possible, of which a short, non-comprehensive overview is given here: the EPR and TRNSYS use different algorithms to assess the solar gains; heat transfer through transmission is modelled differently (TRNSYS uses the transfer functions of Mitalas and Arseneault (1972), while the Belgian EPR uses the heat transmittance coefficient under static conditions (NBN B 62-002 1987)); the Belgian EPR uses fixed radiative heat transfer coefficients to assess the internal and external radiation, while TRNSYS models both radiations in a more explicit way (see 4.2); the heat transfer via the ground is modelled differently: in

TRNSYS the implementation is based on NBN EN ISO 13370 (2008) (see 4.3.3) while in the EPR method most often a simple reduction factor is applied to the floor slab U-value (Transmissiereferentiedocument (2010)).

In order to get insight in the extent of the aforementioned differences, the detailed method is locally adapted in order to obtain an outcome comparable to the EPR method: (i) all day- and night reference indoor temperatures are continuously set to 18 °C, (ii) window opening ventilation rates are set to 0, (iii) internal heat gains and infiltration and ventilation air flows are adapted to those from the EPR, (iv) the net energy demand is derived via Equation 5.11 with $E_{losses,m}$ and $E_{gains,m}$ extracted from the TRNSYS-simulation (implying that the heat supplied by the ideal heating equipment is not used as net energy demand), (v) the ideal cooling equipment of the building model is now switched on, preventing the indoor temperature from rising above 18 °C and as such assuring that the transmission and convective losses ($E_{losses,m}$) correspond to those under a constant indoor temperature regime and (vi) the energy use for space heating is determined by applying the constant heatin system efficiencies from the EPR method.

Figure 5.17 shows the comparison with the EPR method for the 7 fictitious dwellings in open typology. The differences are small, certainly for the poorly insulated dwellings. This indicates that the discrepancies between EPR and detailed method, observed in the following subsections, are only limitedly determined by the (modelling) aspects like different transmission heat transfer modelling or solar gains assessment and/or that these aspects cancel each other out in the global comparison.

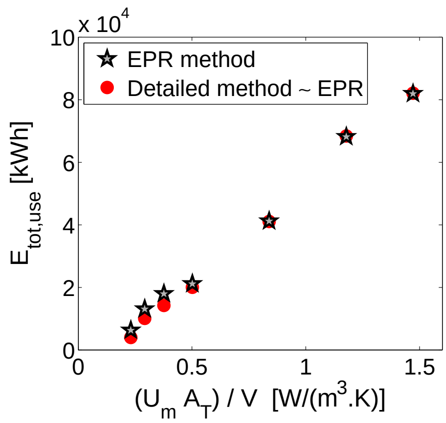


Figure 5.17: Annual energy use for space heating: the EPR method compared to the detailed method in TRNSYS, adapted to be comparable to EPR, for the 7 fictitious dwellings in open typology.

5.5.2 Indoor temperatures

In the EPR method the whole dwelling is assumed to be continuously heated at 18 °C. When comparing that 18 °C with the monitored indoor temperatures in the Lijsterlaan and the monitoring campaign described in Janssens and Vandepitte (2006) (see 5.4.1), it is evident that 18 °C proves to be a systematic overestimation of nightzone temperatures in winter conditions −certainly in poorly insulated dwellings. In addition, due to the intermittent and zonal heating, the indoor temperature will rise when moving towards better insulation levels −even when the original user behaviour is maintained. As already mentioned in Chapter 2 and as investigated by Deurinck et al. (2012), this (inevitable) temperature rise is called the *physical part of the temperature takeback* and cannot be taken into account when assuming a fixed indoor temperature throughout the whole dwelling whatever its insulation level. Figure 2.4 is resumed here in Figure 5.18 and shows how the detailed method is able to capture those physical mechanisms that eventually determine the indoor temperature in dwellings. Again also the influence of the heating pattern in the nightzone is clearly visible in the strong skewness of the boxplots for the poorly insulated dwellings.

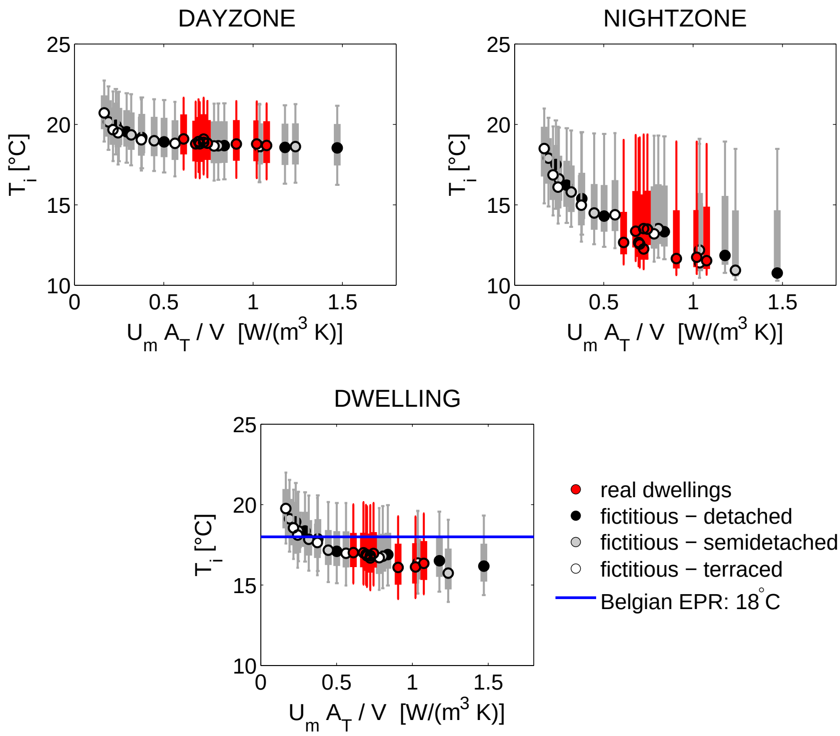
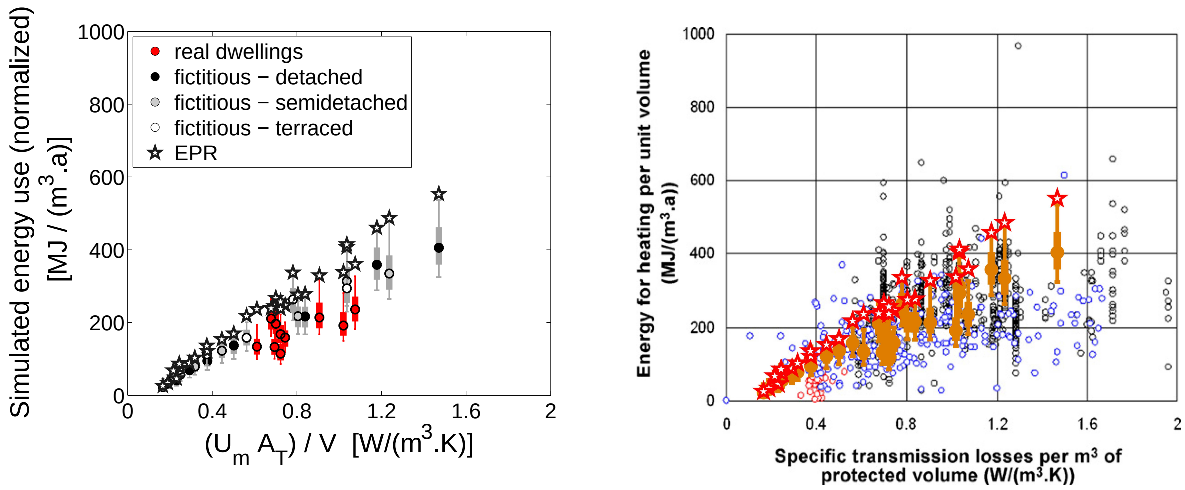


Figure 5.18: Indoor temperature[a] at T_e = 5 °C as a function of specific transmission heat losses ($U_m A_T$ [W/K]) per m^3 heated volume (V [m^3]).

[a]Marker = median of detailed method; box = 25th until 75th percentile; whiskers = 10th until 90th percentile

5.5.3 Energy use for space heating

The total heating season energy use for space heating following the above Belgian calculation method is determined for all 10 real and all 21 fictitious Lijsterlaan dwellings (Figure 5.19a). Compared with the previously shown energy uses for space heating (Figure 5.16a) the EPR energy uses are significantly higher. In Figure 5.19b and similarly as above, the comparison is made with the measurement data of Hens et al. (2010). The EPR points are definitely at the higher end of the measured data scatter cloud, illustrating again how an energy labelling tool is not designed to estimate actual energy uses.



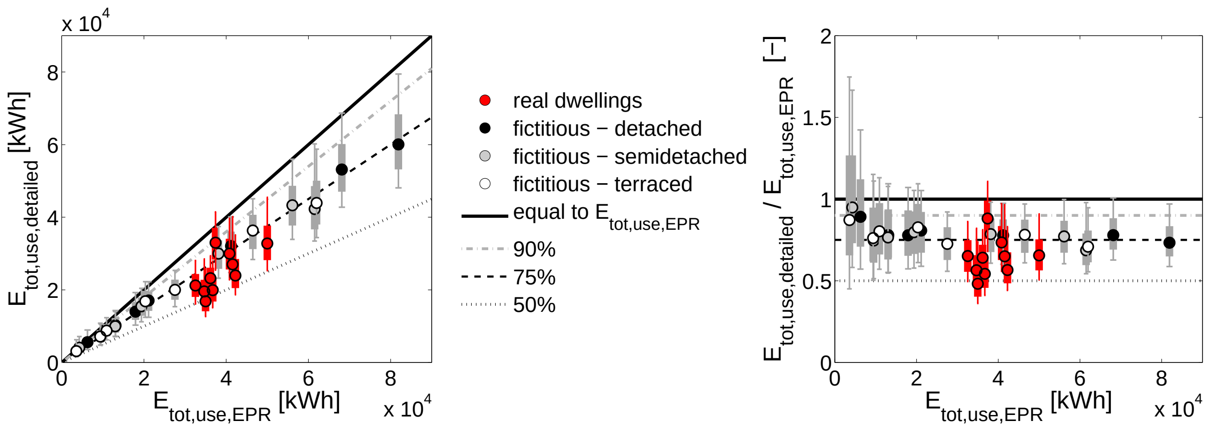
(a) Simulated results only[a]

(b) Simulated results (orange: detailed method; red stars: EPR method) projected onto Hens et al. (2010).

[a]Marker = median of detailed method; box = 25th until 75th percentile; whiskers = 10th until 90th percentile

Figure 5.19: The energy use for space heating per year per unit volume [MJ/(m^3.a)] for the detailed method and the EPR method: (a) simulated results and (b) compared to measurement data as found in Hens et al. (2010) (b).

The difference between the detailed and EPR method is shown directly in Figure 5.20. When looking at the poorly insulated dwellings, it is visible how the median energy uses of the detailed method are between 50 and 75 % of those from the EPR method. In reality, measured energy uses of poorly insulated dwellings prove to be about 50-60 % from those calculated (see section 2.4.3). This suggests that the detailed method is able to reduce a significant part of the gap between measured and calculated energy use. Furthermore, it is quite unlikely that in the poorly insulated dwellings the heating behaviour will be that of the upper parts of the error bars, reflecting rather



(a) $E_{detailed}$ at Y-axis

(b) $E_{detailed}/E_{EPR}$ at Y-axis

Figure 5.20: Total energy use for space heating: the detailed method[a] *compared to the Belgian energy performance calculation (EPR).*

[a]Marker = median of detailed method; box = 25th until 75th percentile; whiskers = 10th until 90th percentile

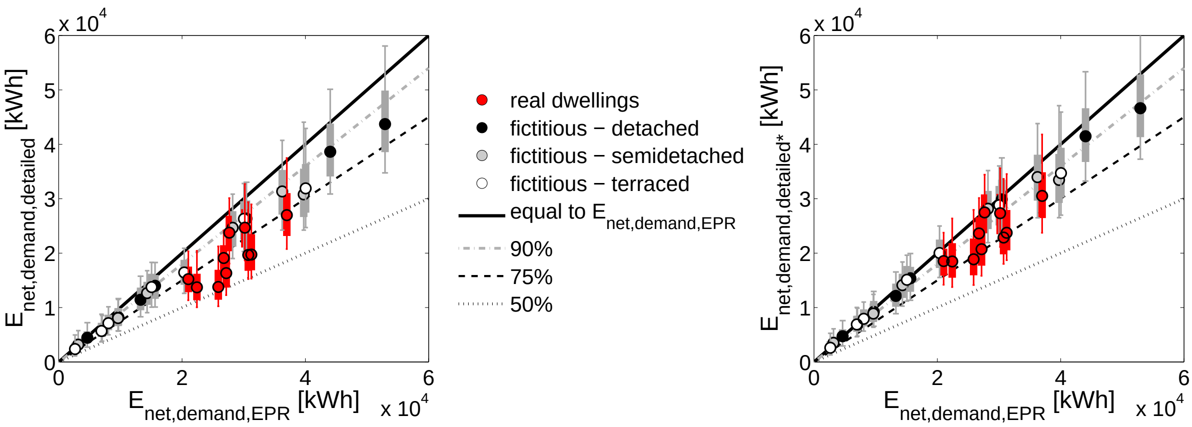
wasteful heating behaviour. Instead, more economic heating behaviour is expected[5] leading to larger deviations with the EPR method. Again, the real dwellings seem to deviate from the fictitious dwellings as the EPR method overestimates their energy use for space heating to a greater extent. This will be further elaborated at the end of this subsection.

When looking at the very well insulated dwellings (best visible at Figure 5.21b), the differences between both methods get smaller, with about half of the user profiles leading to a higher outcome than the EPR outcome for the best insulated fictitious variants in all three typologies. Given that the indoor temperatures of those well insulated dwellings very well approach the 18 °C of the EPR and even lie above, as shown in Figure 5.18, this should not come as a surprise.

In order to keep track of what influences the above deviation between detailed and EPR method, the comparison is decomposed in two steps in Figure 5.21, thereby keeping the net energy demand of the EPR method at the X-axis.

Firstly, the influence of the different heating system efficiencies is eliminated by only looking at the net energy demand - see Figure 5.21a. The deviation between both methods decreased, indicating how the different heating system efficiencies of both methods take up a significant share of the observed difference in Figure 5.20. This is as expected: while the EPR method uses constant overall heating system efficiencies throughout the year (0.74 and 0.65 for condensing and non-condensing boiler in hydronic heating systems with radiators and central room thermostat), the detailed method relies on the performance curves of Peeters et al. (2008), shown in Figure 4.8 and predicting higher

[5]As discussed in Chapter 3 empirical evidence is found that both household and building characteristics (like the thermal insulation quality) affect which rooms are heated and when.



(a) $E_{net,demand,detailed}$ at Y-axis

(b) $E_{net,demand,detailed*}$ at Y-axis: infiltration and ventilation air flows from EPR

Figure 5.21: Total net energy demand for space heating: (a) detailed method[a] and (b) detailed method[a] when the infiltration and ventilation modelling of the EPR method are taken over, both plotted against the EPR method.

[a]Marker = median of detailed method; box = 25th until 75th percentile; whiskers = 10th until 90th percentile

overall heating system efficiencies (0.82 and 0.73 for the same systems respectively and in case of annual net energy demand > ~20 000 kWh).

Secondly, the net energy demand is again calculated following the detailed method, yet by taking over the air flow modelling of the EPR method (see 5.5.1). The result is shown in Figure 5.21b. Now the deviation further decreased, implying that the lower infiltration losses of the EPR method (making the boxplots in Figure 5.21a to move downwards) are counteracted by the higher hygienic ventilation losses (making the boxplots to move upwards). The observed difference in Figure 5.21b is now due to the different user behaviour modelling of the detailed method (intermittent and zonal heating, different internal heat gains modelling and window opening behaviour), together of course with the remaining modelling issues as discussed in 5.5.1. Still though in Figure 5.21b, the net energy demands from the (adapted) detailed method are only about 75 to 90 % of those from the EPR method, highlighting how a more realistic implementation of user behaviour reduces the computed net energy demand. Furthermore, it must be kept in mind that the probabilistic behavioural model of the detailed method does include window opening behaviour, while the EPR method does not. If the adopted window opening behaviour ventilation rates eventually turn out to be too high, the differences in Figure 5.21b would become larger.

In order to solely see the effect of the intermittent and zonal heating on the net energy demand Figure 2.5 is replicated in Figure 5.22, showing the net energy demands of the (original) detailed method against those from the detailed method in which all day- and nightzone reference indoor temperatures are continuously set to 18 °C, leaving all other parameters of the behavioural model unaltered. The observed difference is now solely due to whether or no intermittent and zonal heating is modelled and demonstrates how doing so easily reduces the net energy demand by about 10 to 25 %.

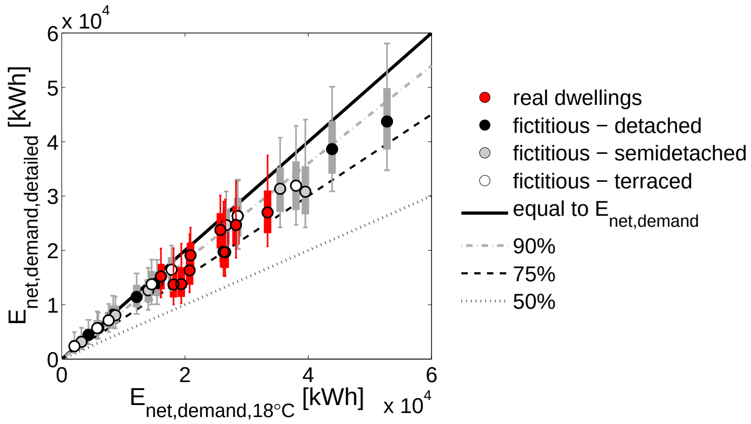


Figure 5.22: Total net energy demand for space heating: detailed method[a] against the mean outcome of detailed method when continuous heating at 18 °C is applied; with all other parameters from the behavioural model unaltered).

[a]Marker = median of detailed method; box = 25th until 75th percentile; whiskers = 10th until 90th percentile

A final, yet important, comment must be made concerning the EPR method overrating the energy uses for the real dwellings (red boxplots in all previous figures) to a larger extent than they do for the fictitious dwellings. The reason is the 'uneven' spread of the thermal insulation in the real dwellings. These dwellings have less well insulated nightzones (higher U_mA_T/V-values) and better insulated dayzones (lower U_mA_T/V-values) than the fictitious dwellings, shown in Figure 5.23.

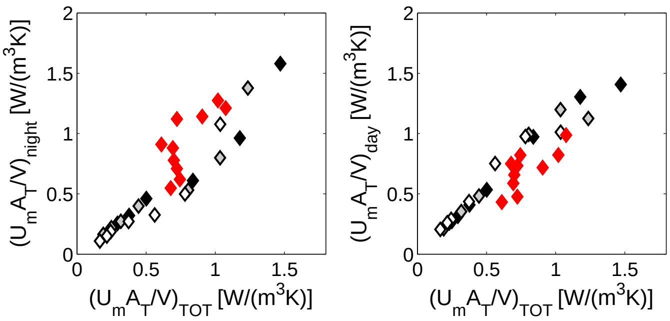
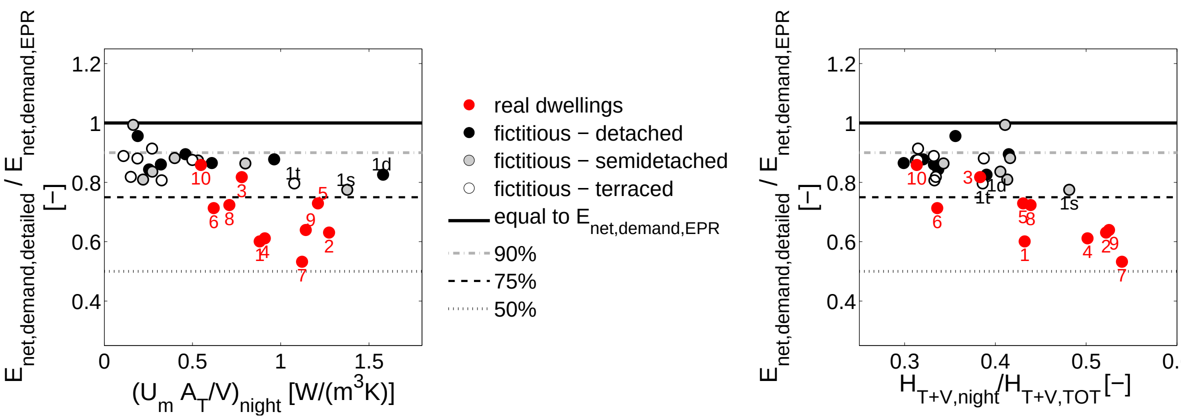


Figure 5.23: U_mA_T/V-values [W/(m^{3}K] of the nightzone (left) and dayzone (right) as a function of the U_mA_T/V-value of the dwelling, for all real dwellings (red markers) and all fictitious dwellings (black, grey and white).

The more a nightzone is poorly insulated, the more its indoor temperature will deviate from the 18 °C assumed by EPR, leading to a larger overestimation of actual dwelling net energy demand. This is shown in Figure 5.24a, where the ratios $E_{net,demand,detailed}/E_{net,demand,EPR}$ from Figure 5.21a are shown as a function of the U_mA_T/V-value of the nightzone (the boxplots of the y-values are not shown in order not to overload the figure; the numbers of the real dwellings refer to those in Table 4.4 page 117).

However, the insulation quality of the nightzone alone is not the only explanation; when looking at the 3 least insulated fictitious dwellings, also numbered in Figure 5.24a, they have similarly high U_mA_T/V-values of the nightzone, and nonetheless a smaller overestimation by the EPR method. The reason must be sought in how the nightzone insulation quality relates to the overall insulation



(a) (b)

Figure 5.24: The difference between detailed and EPR method is determined by the spread of insulation throughout the dwelling: median values of Figure 5.21a as a function of (a) the nightzone U_mA_T/V [W/(m^{3}K)] and (b) the ratio of night over dwelling specific transmission and ventilation losses $H_{T+V,night}/H_{T+V,TOT}$ [-], with $H_{T+V} = \Sigma U_iA_i + \rho_a c_a(v_{inf,EPR}A_T + n_{vent,EPR}V)/3600$ [W/K].

quality of the dwelling. This can be quantified by looking at the specific transmission and ventilation losses $H_{T+V} = \Sigma U_i A_i + \rho_a c_a(v_{inf,EPR} A_T + n_{vent,EPR} V)/3600$ [W/K] of the nightzone against those from the total dwelling (for $v_{inf,EPR}$ and $n_{vent,EPR}$ see equations 5.8 and 5.9 respectively) . This ratio is given at the x-axis of Figure 5.24b.

Now the 3 least insulated fictitious dwellings, with both day- and nightzone poorly insulated, move to the left and the tendency gets more unequivocal: the more a nightzone −theoretically− contributes to the dwelling transmission and ventilation losses, the more an overestimation of actual nightzone heating behaviour (like done by EPR) will result in an overestimation of total dwelling net energy demand. A large contribution of a nightzone, in relative terms, is achieved not only through its own characteristics (higher U-values, heat loss area and/or volume) but also through the characteristics of the dayzone: the more a poorly insulated nightzone is 'combined' with a well insulated dayzone, the higher $H_{T+V,night}/H_{T+V,TOT}$.

The real dwellings of the Lijsterlaan illustrate why the above issue is important in a housing stock context. It is current practice in Belgium to renovate a dwelling, thereby enlarging the dwelling's living area by adding a newly-built extension. As these extensions are most often better insulated than the original dwelling, an imbalance exist in the spread of the insulation throughout the dwelling, affecting the ratio $H_{T+V,night}/H_{T+V,TOT}$ towards higher values and as such easily leading to an overestimation of actual net energy demand. It highlights the major feature of the two-zone building model with a zone-dependent behavioural model: whereas the one-zone assumption of the EPR method values every insulation thickness equally and independently of its location in the building envelope, the two-zone modelling rightfully benefits insulation placed in the intensively heated dayzone and tempers the influence of the abscence/low levels of insulation in the scarcely heated nightzone.

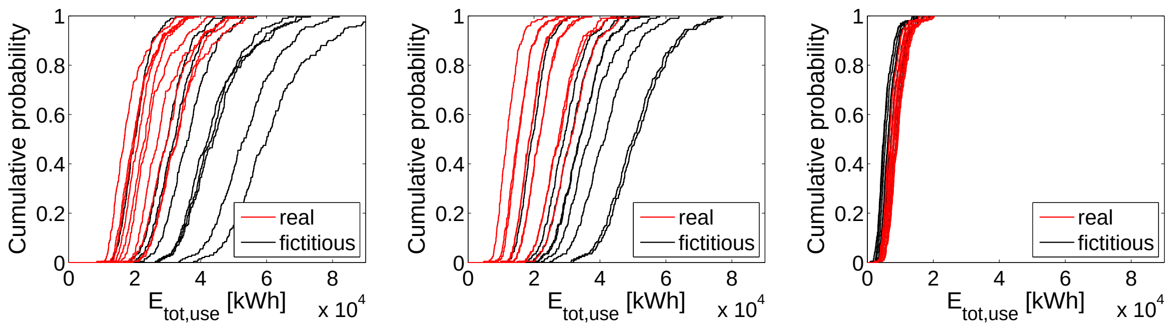
5.5.4 Energy savings

Above it is shown how the EPR method easily overestimates the pre-retrofit energy use of the detailed method by 25 %. What could be argued as still being a reasonable difference in terms of energy use, can however have a great impact on the energy saving prediction. This is illustrated here by comparing the predicted energy savings for both methods. To do so, two retrofit measures are simulated for all 10 real Lijsterlaan dwellings and the variants 1 to 3 of the fictitious Lijsterlaan dwellings (see Table 4.5):

- a 'minor' retrofit in which all roofs (pitched, flat and ceiling towards the unheated attic) are insulated to a mineral wool thickness of 0.20 m, and
- a 'major' retrofit in which also the walls and the floors are insulated to an insulation thickness of 0.06 m PUR and 0.10 m PUR respectively, all windows are replaced by highly insulating glazing (U = 1.06 W/(m^{2}K); g-value = 0.59) in wooden profiles, the air permeability is assumed to drop to n_{50} = 1 h^{-1}, all boilers are replaced by condensing gas boilers and a balanced ventilation system with a heat recovery unit is installed. The resulting U_m is then about 0.36-0.44 W/(m^{2}K), $U_m A_T/V$ about 0.20-0.44 W/(m^{3}K).

Detailed method

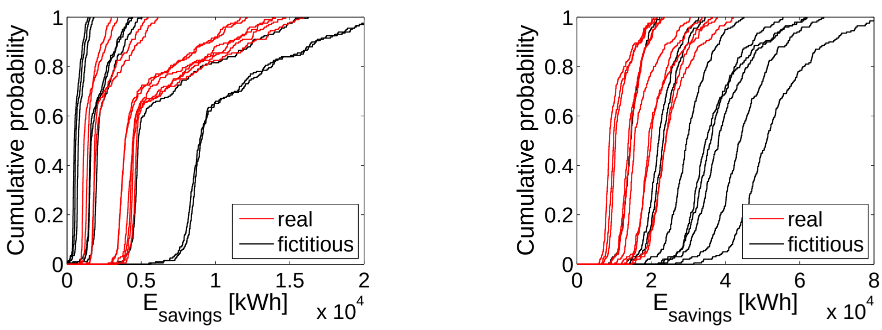
Figure 5.25 shows the cumulative distributions of the total heating season energy use for space heating. These curves show both the influence of the insulation levels (visual in the lateral displacement of all curves along the x-axis) and the impact of user behaviour (the steeper the curves, the lower the impact of the user behaviour). For example, despite the fact that well insulated dwellings proved to be more sensitive to the user behaviour parameters than a poorly insulated dwelling (see 5.3), it of course does not imply that user behaviour is more important in absolute terms. The curves before retrofit are clearly flatter than the ones after retrofits, indicating that the pre-retrofit dwellings undergo much larger absolute variability than post-retrofit dwellings.



(a) Before retrofit *(b) After minor retrofit* *(c) After major retrofit*

Figure 5.25: Cumulative plots of total heating season energy use for space heating, when fictitious retrofits are applied to all real and a selection of fictitious dwellings (1 → 3).

The resulting cumulative distribution functions of the energy savings are shown in Figure 5.26. When looking at the roof insulation retrofit of Figure 5.26a, the impact of user behaviour becomes strikingly clear. The distribution curves display a distinct shift-point, similarly as the shiftpoint in the nightzone temperature of Figure 5.3 and dividing those users who never heat the nightzone (steep lower part of the distribution) from those who do heat the nightzone (either only at setback temperature during the night either identically to the dayzone). While this division did not seem to greatly influence the total energy use for space heating of Figure 5.3, it does influence the calculated energy



(a) Minor retrofit *(b) Major retrofit*

Figure 5.26: Cumulative plots of energy savings for space heating, when fictitious retrofits are applied to all real and a selection of fictitious dwellings (1 → 3).

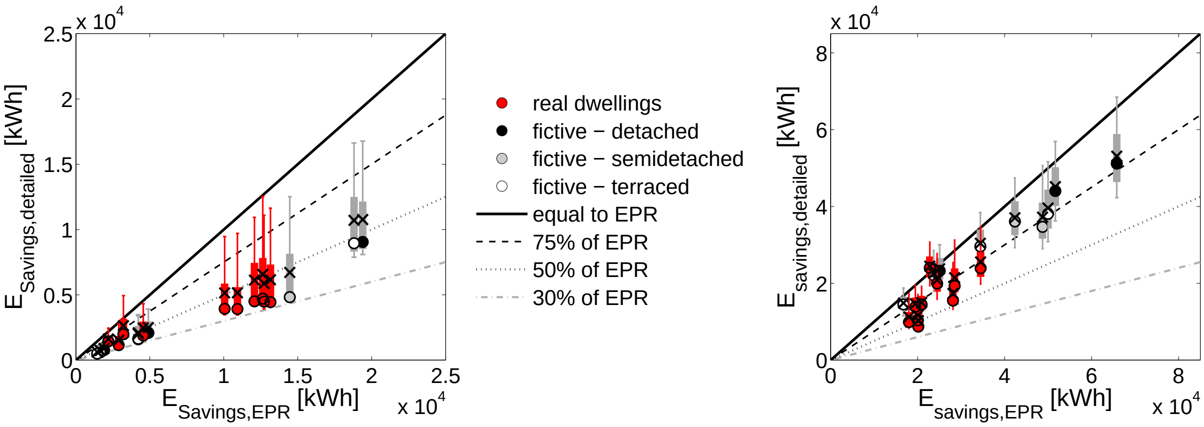
savings here. For the Lijsterlaan dwelling the largest roof area is situated above the nightzone. If it is not heated, the energy savings following a roof insulation measure will therefore be quite low and only limitedly influenced by temperature setpoints and time schedules in the dayzone (steep curve). If however one chooses to heat the nightzone, the potential for saving energy is higher and more influenced by the nightzone heating behaviour (see flatter second part of curves). Logically, the shifting point is more pronounced for those dwellings without initial roof insulation (all curves at the right). Of course, all depends from the rather artificial division and assumptions made for PATTERNNIGHT so the question remains whether it occurs in reality in this extent. However, it does illustrate how heating patterns can have a great impact on the actual energy savings.

For the more holistic major retrofit of Figure 5.26b the clear division of users depending on their nightzone heating behaviour is less pronounced. As the building envelope is insulated more uniformly now, the influence of whether or not the nightzone heated is reduced and mixed up with all other behavioural variables. Still, the user behaviour strongly determines the actual energy savings, because savings can almost differ by a factor two solely depending on who is to inhabit the dwelling (see for instance most right curve of 5.26b).

Comparison with EPR method

In Figure 5.27 the savings of the detailed method are compared to those from the EPR method.

Concerning the roof insulation of the minor retrofit of Figure 5.27a, the major feature of the two-zone building modelling gets immediately clear. When the nightzone is not heated (~ median of boxplot), the detailed savings are only between 30 to 50 % of the EPR savings. The one-zone assumption of the EPR method also assumes 18 °C in the nightzone and thus inevitably overestimates the energy saving potential of the roof insulation. And even when the nightzone is heated identically to the dayzone (~ top of boxplot), the detailed savings are still about 20 % lower than EPR due to the overestimated pre-retrofit energy use of Figure 5.20.



(a) Minor retrofit

(b) Major retrofit

Figure 5.27: Energy savings for space heating: the detailed method[a] against the Belgian energy performance calculation (EPR) .

[a]Circle = median, black cross = mean; box = 25th until 75th percentile; whiskers = 10th until 90th percentile

When looking at the more thorough major retrofit of Figure 5.27b, again the boxplots have a more symmetric shape due to the smaller influence of the nightzone heating behaviour. The detailed method now predicts savings that are about 50 to 75 % of the EPR savings for most real dwellings and about 75-90 % for the fictitious dwellings. The larger overestimation of savings by EPR for the real dwellings is due to the larger overestimation of initial energy use by EPR as described previously.

The above analysis denotes how the detailed method clearly predicts lower energy savings than the Belgian EPR method. For the two retrofits considered it generates energy savings that are only 70 to 50 to even only 30 % of those from the EPR method. Suppose the detailed method is a reasonable representation of actual energy use and savings, this would correspond to shortfall values of 1-$\Delta E_{detailed}/\Delta E_{EPR}$ (see Equation 1.1) from to 30 to 70 %. With actual shortfall being in the range of 20 to 60 % (see Chapter 2), the detailed method seems to be able to reduce a significant part of shortfall. Of course, this comparison alone is no conclusive evidence of the detailed method being able to predict reliable energy savings. Nevertheless, it does confirm that the detailed method should be seen as an improvement compared to the EPR method and vice versa, that the savings calculated by EPR tend to give false results and as such contribute significantly to actual shortfall.

5.6 Conclusion

This chapter has focused on the evaluation of the behavioural and building model, developed in the two previous chapters.

A preliminary analysis denoted how both the energy use for space heating and the indoor temperature are heavily affected by the behavioural model. So, if one does not know who is to inhabit the dwelling, huge errors are possible in estimating the energy use and indoor condition of individual dwellings.

Based on a reference output of 3000 simulations it is investigated which minimal sampling size is needed to obtain a reliable estimation of the total heating season energy use for space heating and the indoor reference temperature at T_e = 5 °C. Given a space-filling Latin Hypercube sampling design, it is concluded that 200 runs is a safe sample size to reliable estimate not only the mean and median of both output distributions, but also the 10th and 90th percentile values.

A sensitivity analysis is performed in the literal sense of the word: what is the effect on the output due to small changes in the input values –independently of the likeliness of those changes? To do so, normalised sensitivity indicators $\hat{\beta}_i$ are calculated through multiple linear regression, allowing for a -be it limited- comparison between different behavioural and building-related parameters. Independently of the insulation quality, a dwelling's energy use for space heating is equally sensitive to small changes in the heating set-point temperature as it is to changes in the heating system efficiency. Also, a well insulated dwelling proves to be sensitive to many more parameters (like internal heat gains, ventilation rates and orientation) than a poorly insulated dwelling. Finally, the obtained sensitivity indicators proved to be in reasonable accordance with literature values of other residential building models.

Though interesting, the sensitivity analysis alone provides only limitedly useful conclusions due to the missing link with actual occurring variabilities. Therefore, an uncertainty analysis is performed by computing Spearman's rank correlation coefficients between the energy use and the behavioural parameters, of which the input variabilities are quite well-known and documented. The most important parameter, whatever the insulation quality, proves to be the setpoint temperature in the dayzone. Other predominant parameters, certainly in the poorly insulated dwelling, are the setback temperature, when setback is applied and how the nightzone is heated. Unfortunately, many assumptions had to be made to construct the heating behaviour in the nightzone, turning the latter into a critical parameter of the behavioural model. As expected, the internal heat gains and window opening behaviour are more dominant in the well than in the poorly insulated dwelling −even if much lower window opening air change rates are adopted than foreseen in the original model. Certainly for the well insulated dwelling, the window opening behaviour turns out to be a critical parameter, requiring additional research to clarify its true extent. Finally, also the occupancy profiles have their share in the overall outcome: a higher degree of occupancy leads to higher energy uses in a poorly insulated dwelling through the longer heat demand periods, whereas it leads to lower energy uses in a very well insulated dwelling through its link with internal heat gains.

The output, computed for 10 real and 21 fictitious dwellings, is compared to measurements. For the main living room temperatures −where temperatures are predominantly driven by the heating behaviour− a very satisfying agreement is found between measurement and modelled data. This undersets that the behavioural model is well able to capture the heating behaviour in the main living rooms. A smaller correspondence is found between the modelled and measured temperatures in the nightzone. Many explanations are given, none of which can be said to have predominant impact.

When the calculated energy uses for space heating are compared to individual cases, large individual errors are found, denoting how the here developed methodology is not meant to predict the energy use in specific single cases. When however they are compared to a large-scale Belgian measurement campaign, a very satisfying correspondence is found. Good confidence is thus given that the here developed methodology is able to generate reliable energy uses −not on the individual dwelling level, but on a more aggregated scale.

At last, the output is compared to the Belgian energy performance assessment regulation (EPR). The here developed methodology generates energy uses for space heating that are, on average and for barely insulated dwellings, about 25 % lower than those from the EPR. As soon as dwellings are better insulated, both methods correspond better. Interestingly, it was shown how not only the nightzone insulation level itself plays an important role in the amount of overestimation by the EPR method, but also how its level relates to the overall dwelling insulation quality: the larger the imbalance between night- and dayzone insulation quality (as for instance typically the case for dwellings having a better insulated extension added to the heated dayzone), the more the EPR method overestimates the net energy demand.

In the case of only insulating the roof areas −still a popular retrofit measure in Belgium− the energy savings of the detailed method prove to be only 30 to 50 % of those from the EPR, corresponding to a large shortfall in expected energy savings of 70 to 50 %. In the case of a more thorough renovation of the building envelope, the energy savings of the detailed method are about 75 % of those from the EPR, corresponding to 25 % shortfall. As actual shortfall is found to vary between 20 to 60 %, this can serve as an encouraging indication that the here developed methodology is able to account for a significant part of it. At the same time this should be seen as a clear indication that the savings calculated by EPR tend to give false results and as such contribute significantly to shortfall. It highlights how the energy performance gap, defined as the difference between actual and EPR predicted energy use (Chapter 2), should not be forgotten when evaluating shortfall, thereby possibly reducing the often cited impact of other factors like the rebound effect and technical shortcomings.

6

Towards reliable energy saving predictions at aggregated level

Policy makers heavily rely on housing stock models to get insight in the energy saving potential of different retrofit measures. In the previous chapters, the main focus is put on a the reliable assessment at dwelling level, by including evidence-based user behaviour in a two-zone generic building model. In this chapter it is illustrated how both the behavioural and building model can be implemented and used within a probabilistic housing stock framework.

6.1 Introduction

At the aggregated level (city, district, regional, national, . . .) different actors are interested in the effect of possible retrofitting measures on the total energy use of a housing stock: policy makers, local authorities, (social) housing companies, energy saving companies (ESCo), . . . To do so, they heavily rely on models, estimating the energy saving potential of the housing stock considered. It is thus essential that robust and accurate models are available to inform and evaluate specific (policy) measures (Kavgic et al. 2010). Amongst other criteria like transparency and (reasonable) ease of use, these models should be able to reliably estimate the 'baseline' energy use of the housing stock they are modelling (Kavgic et al. 2010) and quantify the level of uncertainty regarding their predictions (Booth et al. 2011). Both criteria are dealt with in this chapter.

First, the probabilistic behavioural model and generic building model, developed in this dissertation, are valuable contributions to a more reliable estimate of the 'baseline' housing stock energy use. Not only because they allow for a more realistic estimation of dwelling energy use (compared to the often used energy labelling tools −see Chapter 5), but also because the probabilistic framework and generic building set-up provides in an elegant way to capture the large heterogeneity that is inherent to housing stocks. Two major sources of heterogeneity can be identified: (i) user behaviour and (ii) dwelling characteristics (typologies, geometries, insulation levels, heating systems, etc.).

Following the literature review in Chapter 3, the wide variety in user behaviour is evident. As the user behaviour patterns can range from energy-saving to energy-wasteful, it is important to map these patterns and include them in a housing stock framework. While the probabilistic behavioural model of Chapter 3 is an attempt to do so, a similar attempt should be made to capture the dwelling variability.

Typically, the large dwelling variability is approached via the *archetype technique*, dividing the housing stock in groups of 'similar' dwellings and attributing a single archetype building model to each of these groups. This is most often done based on the age-typology division, for instance grouping all detached houses built between 1946-1970. Even within such an apparently homogenous group of dwellings, however, large variations are possible (see further 6.3). Not only because different geometries, sizes, orientations etc. are detected, dating back to the time of construction, but also because in the meanwhile retrofits have been carried out, thereby upgrading the average insulation level of this group. Certainly when estimating the energy saving potential of the housing stock, this is important knowledge. For instance, before the oil crisis of 1973, insulating dwellings was no part of common building practice (Hens et al. 2001). If however a significant part of the detached dwellings built between 1946-1970 have already undergone, say, roof insulation since time of construction, the expected corresponding energy savings for this group of dwellings are consequently lower than solely expected based on the construction period.

In this chapter, a technique is proposed and investigated to capture the user behaviour and dwelling variability simultaneously within the developed probabilistic framework. Due to the generic set up of the building model and the available probabilistic behavioural model, this so-called *stochastic* technique proves to be an elegant and straightforward way of generating an aggregated output, independently of the scale desired (city/district/regional/national).

Second, a housing stock model also has to deal with quantifying the uncertainty regarding its predictions. Throughout the housing stock modelling process many assumptions are to be made, not only due to lack of appropriate input data but also due to sometimes arbitrary simplifications in the assessment of actual physical processes and in the incorporation of the large aforementioned variability. Certainly when aiming for the housing stock model to be used as policy-making tool, it is important to address how these assumptions weigh on the final outcome. Therefore, this chapter will end with a short overview of how uncertainty is currently dealt with in housing stock models and will set out a global framework allowing to quantify the inherent uncertainty of housing stock models.

Outline of the chapter

A concise state-of-the-art concerning housing stock modelling is given first, together with current ways of dealing with the housing stock variability (6.2). Afterwards, the aforementioned stochastic technique is described and compared to the ways nowadays dwelling variability is incorporated in housing stock models (6.3). Finally, the uncertainty quantification within housing stock models is discussed (6.4).

6.2 Housing stock models

6.2.1 Global overview

Much of the information following here results from the detailed reviews of existing housing stock models by Swan and Ugursal (2009) and Kavgic et al. (2010). Only a concise summary is given here.

Broadly seen, the housing stock models can be divided into three main groups, each with their specific features and (dis)advantages: top-down models, statistical bottom-up and engineering based bottom-up models. The main features and disadvantages of all three methods are summarized in Table 6.1.

The **top-down** models work at a strongly aggregated level, typically aimed at fitting a historical time series of national energy consumption or CO_2 emissions data to macroeconomic indicators

Table 6.1: Benefits and limitations of the three categories of housing stock models −taken over from Kavgic et al. (2010).

Top-down	Bottom-up statistical	Bottom-up engineering based
BENEFITS		
• Focus on interaction between energy sector and economy at large	• Include macro- and socioeconomic effects	• Describe current and prospective technologies in detail
• Capable of modelling relationships between different economic variables and energy demand	• Able to determinate typical end-use energy use	• Estimate least-cost combination of technological measures to meet given demand
• Avoid detailed technology descriptions	• Easier to develop and use	• Enable policy to be more effectively targeted at use
• Able to model impact of different social cost-benefit energy and emission policies and scenarios	• Do not require detailed data	• Assess and quantify impact of different combination of technologies
• Use aggregated economic data		• Use physically measurable data
LIMITATIONS		
• Depend on past energy economy interactions to project future trends	• Do not provide much data and flexibility	• Poorly describe market interactions
• Lack the level of technological detail	• Have limited capacity to assess impact of energy conservation measures	• Neglect relationships between energy use and macroeconomic activity
• Less suitable for examining technology-specific policies	• Rely on historical consumption data	• Require large amount of technical data
• Typically assume efficient markets and no efficiency gaps	• Require large sample	• Determine human behaviour by assumptions
	• Multicollinearity	

like price indices, income, employment rate, fuel prices, ... Examples can be found in Haas and Schipper (1999), Bentzen and Engsted (2001). These models do not consider the energy use of separate dwelling units in detail, but try to capture the complex relations between the energy sector and the economy at large by regressing the trends throughout the years. As such, they are able to account for the consequences following for instance a changing economic climate or a small increase in housing construction units. However, due to their dependence on historical data and their inability to correctly represent future technological improvements, these top-down models are only limitedly helpful for robust decision and policy making in the context of retrofitting scenarios.

The **statistical bottom-up** models work on a more disaggregated level by relying on a large set of historical end-energy uses of individual dwellings (typically obtained via billing data) and fitting those with (simple) survey information. Typical techniques to do so are regression, conditional demand analysis and neural network (Swan and Ugursal 2009). Examples are found in Aydinalp-Koksal and Ugursal (2008), Mastrucci et al. (2014). These models are relatively easy to develop, intrinsically account for the different user behaviour within the building stock and in itself include also those energy loads that can remain unspecified in the bottom-up engineering based methods (see further). As such, they are often more accurate than the engineering based methods (Booth et al. 2011). However, they do not provide much detail and flexibility and have restricted capacity to evaluate the impact of energy conservation scenarios (Fung 2003).

The **engineering based bottom-up** models calculate the energy use for a set of individual or groups of houses by means of a building energy calculation method (from highly simplified to very complex) and then extrapolate these results to represent the region or nation (see for instance Hens et al. (2001), Firth et al. (2010), Cheng and Steemers (2011), Mata et al. (2014)). The typical workflow is shown in Figure 6.1.

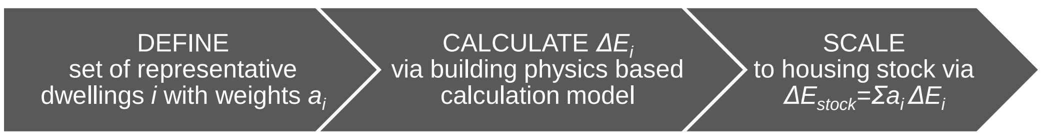


Figure 6.1: Typical workflow within an engineering-based bottom-up housing stock model.

These models are the only one that do not require any historical energy use information. Also, due to their potential to deliver building physics based estimates of the energy use, they are well capable of modelling new technological options. So, if the objective is to evaluate the impact of new technologies, be it regarding the building envelope or building energy services, the only option is to use these bottom-up engineering based methods (Swan and Ugursal 2009). Of course these models also suffer some important drawbacks: they require highly detailed input information (geometries, U-values, efficiencies, air permeabilities, ...), the building energy simulation tool can be quite complex and computationally intensive and it is difficult to include (macro)-economic factors. Also, assumptions have to be made concerning the user behaviour and calibration is often needed to ensure that the calculated energy uses are realistic estimates of actual energy uses.

It is clear how the behavioural and building model as developed in this work are meant to fit within the bottom-up engineering based models. With the user behaviour now being evidence-based whenever possible, the amount of arbitrary assumptions can be reduced. Also, the probabilistic behavioural model avoids to make deterministic choices when imposing user behaviour. Currently, apart from the bottom-up housing stock model of Cheng and Steemers (2011), in which the heating time schedules are linked with the household employment status, no evidence is found in the literature of (probabilistic) user behaviour variability being included in housing stock modelling approaches. The here developed probabilistic behavioural can thus contribute to that.

6.2.2 Two main techniques in the engineering based bottom-up methods

Following Swan and Ugursal (2009) two main techniques currently exist within engineering based bottom-up methods[1]: the *archetype* and the *sample* technique. Both techniques differ in the way they try to capture the wide building variety present within a housing stock.

Archetype technique

The archetype technique is probably the most widely used. It broadly classifies the building stock in groups of similar dwellings (clusters), defines archetype dwellings that are believed to best represent each group, and then obtains the aggregated building stock output by multiplying the output of every archetype with the number of houses per group. This archetype approach is also used in many (Belgian) studies, not to actually build a bottom-up model aiming at estimating the total national residential energy use, but to assess the economical feasibility of possible energy-saving investments at the individual (archetype) dwelling level (Dooms et al. 2008, Janssen et al. 2008, Cyx et al. 2011, Van der Veken et al. 2013). This working method is favorable amongst policy makers, as it is a comprehensible level for reasoning on their policy efficiencies and as it enables to point out those groups of dwellings that need primary attention and/or additional monetary incentives. However, when setting up a housing stock model, the archetype technique can only account for a limited part of the actual housing stock variability, due to the limited amount of archetypes that can be reasonably defined.

Three basic criteria should be distinguished when generating archetypes (Parekh 2005): geometric characteristics, thermal characteristics (building envelope, ventilation and heating systems) and operating parameters (occupant behaviour profiles). As said previously, the operating parameters are seldomly accounted for. While the geometric characteristics are most often assessed via the typology, the thermal characteristics are assigned through the construction period (~age). As done for instance by Hens et al. (2001), Dooms et al. (2008), Cyx et al. (2011), the construction periods are translated into U-values and infiltration rates, reflecting for instance how houses before 1973 (first oil crisis) are assumed to have single glazing and no insulation whatsoever. Whereas that might have been a fair assumption, say, 20 years ago, it is no longer defendable nowadays. A signif-

[1] In their review they also add an additional technique, called *distributions*, but due to the latter only dealing with electrical residential end-use from appliances, it is not discussed here.

icant part of the old and outdated building stock segment has already undergone (thermal) retrofits to a certain extent (see for instance the renovation degree of the Lijsterlaan dwellings, constructed in 1969, in Table 4.4 and the analysis in 6.3 hereunder) and this for a variety of reasons: comfort considerations, increased energy awareness and increasing fuel prices, monetary incentives (subsidies, tax benefits) for undertaking energy-saving measures in the framework of the European Energy Performance for Buildings Directive (EPBD 2010), ... The more recent Belgian housing stock model of Georges et al. (2013) somewhat accounts for the inclusion of recent renovation degrees by adopting an arborescence structure to repartition the different insulation levels, heating systems etc. within the typical age-typology division −see Figure 6.2. However, the authors also admit how, by lack of sufficiently detailed data about the Belgian building stock, many assumptions had to be made to generate a complete arborescence.

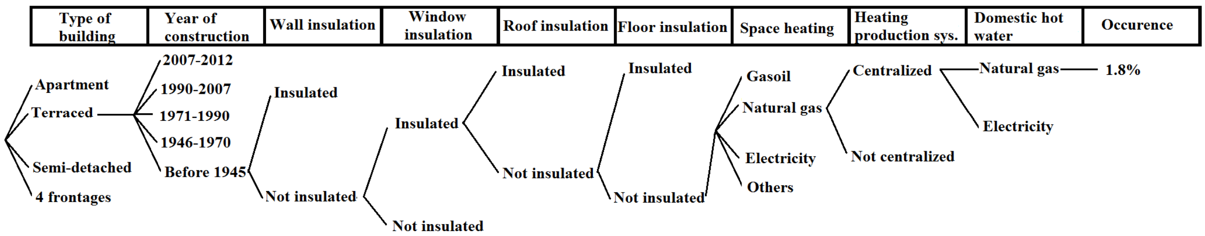


Figure 6.2: Arborescence of Belgian building stock. Source: Georges et al. (2013)

How many archetype dwellings are typically needed to cover the housing stock, remains a major question. All depends of course on the application and housing stock considered. When only looking at the Belgian national housing stock, typically 5 construction periods (e.g. 5 periods in the TABULA-framework (Cyx et al. 2011): pre 1946 / 1946-1970 / 1971-1990 / 1991- 2005 / post 2005) and 4 typologies (detached, semi-detached, terraced and apartment) are considered as first rough division, resulting in 20 base archetypes. As said, these base archetypes are frequently used in the context of cost-benefit analyses on the individual dwelling level. If further refinement is needed to actually compose a bottom-up housing stock, it can easily add up to e.g. 216 dwellings in the Flemish housing stock model of Cyx et al. (2011), 872 dwellings in the arborescence model of Georges et al. (2013) or 960 dwellings in the VerbCO2M-model of Hens (2001).

All previously mentioned studies suffer from a similar artefact concerning the description of the building stock. The reliability of the calculated output heavily depends on the actual representativeness of the archetype dwellings. If these do not sufficiently match the average geometric, thermal and operating characteristics of the group of dwellings they are representing, large divergences are possible. For instance, Parekh (2005) mentions the work of Hamlin (1996), in which the differences were investigated between the energy estimates using the archetypical defaults and actual field surveyed data for 58 houses. The difference in energy estimates ranged from 10 % to 100 % and more. Unsurprisingly, the differences (default values versus the field survey inputs) were marginal for houses which were not retrofitted or improved since their construction. It highlights how the determination of the archetype dwellings must be carefully done, taking at least the past renovation degrees into account and preferably based on large-scale field survey information.

Sample technique

For this technique, actual survey data of a group ('sample') of houses is used as direct input to a building energy simulation model, allowing for each house of the sample to be modelled and calculated individually. Examples are found in Swan et al. (2009), Cheng and Steemers (2011). Provided that the sample size is sufficiently large, this technique allows to capture the wide variety within the housing stock and avoids the (arbitrary) determination process of archetype dwellings. If in addition the sampled houses are representative for the housing stock considered, appropriate weighing factors can be applied to obtain the aggregated housing stock estimate. Of course, this sample technique is more time-consuming (and thus expensive) compared to the archetype technique, not only in gathering the necessary high-resolution field survey data, but also in assuring that the sample is representative for the considered housing stock (see e.g. the thorough statistical analysis in Swan et al. (2009), performed to obtain an unbiased set of sample houses) and in setting-up and running the building energy simulations for each of the sample houses. Hence, its application is limited (Swan and Ugursal 2009) and no such model in a Belgian context is known to the author of this work.

6.3 An additional technique in engineering based bottom-up housing stock models

As said, two main techniques are commonly used to deal with the enormous heterogeneity in the housing stock building characteristics. While the archetype technique provides only a limited representation of the building stock due to the limited variety of archetypes that can be reasonably defined, the sample technique is hampered in its wide-scale use due to its strong dependence on a large and detailed database. Also, if the probabilistic behavioural model is to be used in a bottom-up approach, neither of them are readily capable to include such probabilistic component in a time-efficient way.

Therefore, an additional approach is proposed and investigated here, called the *stochastic* technique. Within this technique, the dwellings are not predefined, but are stochastically composed by sampling their characteristics from probability distributions. The probabilistic behavioural model can easily fit in it, because both user behaviour and building parameters can be sampled within the same sampling scheme. One mainly needs to be bothered about gathering reliable information to construct each of the probability distributions −if possible/relevant complemented with correlation coefficients−, while the sampling scheme itself composes the dwellings and imposes the user. Of course, this technique still requires a large deal of information collection and still relies on (arbitrary) assumptions if data is missing. However, it avoids the expensive and time-consuming task of gathering detailed sample data and can for a great extent rely on existing (statistical) aggregated data, as most commonly used to compose archetype dwellings. Also, the stochastic technique keeps the probabilistic set-up of the behavioural model intact and simply extends the current framework with building parameters, making it a transparent and rather straightforward procedure.

Methodology

The three different techniques (sample, archetype and stochastic) are compared to each other by investigating how they capture the intrinsic user and dwelling heterogeneity of a housing stock.

To do so, a hypothetical housing stock is constructed, being a subgroup of the Belgian housing stock: all dwellings in *open typology built between 1946-1970*. The reason for this subgroup is rather pragmatic, because the Lijsterlaan building model is already available in the current framework and proves to be a fair representation of this group of dwellings (Janssen et al. 2008, Cyx et al. 2011). By only focusing on this subgroup, no additional building models need to be developed.

An important limitation of this working method is that only one geometry, that of the Lijsterlaan dwellings, is considered as being representative for the whole subgroup. Of course, this is not necessarily true: it is probably needed to add other geometries to account for the large variations in geometry (1/2/3 storeys, different width over length ratio, etc.), present even within this subgroup. However, in the context of aiming for a comparison of the three techniques, using only one geometry is sufficient −thereby keeping in mind that by doing so the actual dwelling variability is likely to be underestimated.

Due to the limited representativeness of the small survey campaign of the Lijsterlaan dwellings (see Table 4.4), it is chosen to collect information about the dwelling characteristics by means of the ECS-database. The households in the ECS-survey have been sampled specifically to ensure (Belgian) population representativeness and their dwelling characteristics have been shown to be in excellent agreement with other Belgian surveys (VITO et al. 2012a). Within that database, a subgroup of households is separated, containing only those households living in detached dwellings built between 1946-1970. This subgroup provides the input to all techniques concerning the insulation levels, heating production efficiencies and ventilation systems. Due to the rather limited degree of detail of the ECS-database, assumptions are made to translate the (rough) ECS-information into actual input parameters applicable for the building energy simulations. So, despite the ECS-database being intrinsically representative for the Belgian households and their dwellings, errors are induced through this translation process, yielding a rather hypothetical representation of the actual Belgian '1946-1970 open typology' characteristics. Again, this is no problem for the desired comparison of the three techniques.

Firstly, the ECS-subgroup is shortly analysed to see if and to what extent it differs from the total sample (6.3.1). Secondly, it is described how each of the three techniques captures the subgroup characteristics (6.3.2) and a comparison is carried out (6.3.3). Finally, the feasibility of reducing the computation time is investigated (6.3.4), followed by a concluding discussion (6.3.5).

6.3.1 Subgroup in Belgian housing stock: 1946-1970 - open typology

In the ECS-database a subgroup is separated, representing the 201 households living in detached dwellings, built between 1946-1970. The frequency distributions and correlation coefficients are given hereunder and compared to the total ECS-sample (3396 households).

Frequency distributions

The empirical frequency distributions of the household, heating behaviour and building characteristics are shown in Figures 6.3, 6.4 and 6.5 respectively.

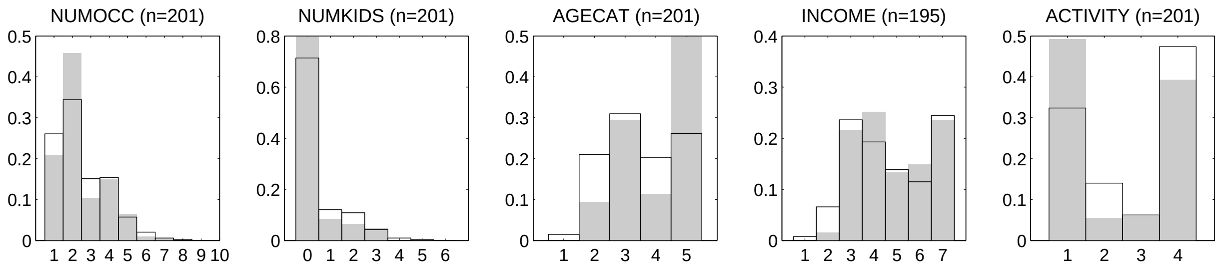


Figure 6.3: Empirical frequency distribution of the (head of the) household characteristics for the subgroup (detached dwelling, built 1946-1970) in the ECS-database. Grey filled: subgroup sample - black lines: total sample. For the explanation of the x-axis: see Table 3.15.

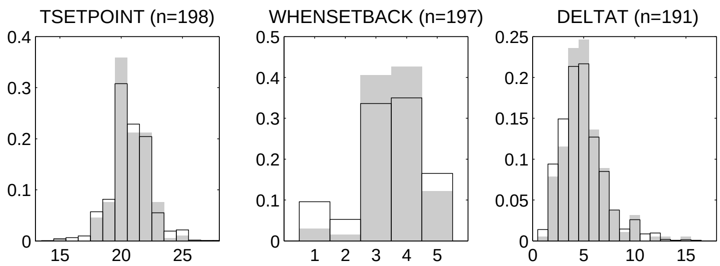


Figure 6.4: Empirical frequency distribution of the user behaviour variables for the subgroup (detached dwelling, built 1946-1970) in the ECS-database. Grey filled: subgroup sample - black lines: total sample. For the explanation of the x-axis: see Table 3.15.

The black lines depict the empirical frequencies of the total ECS sample. One can see how the subgroup of detached dwellings built between 1946-1970 is more frequently inhabited by older and retired persons compared to the total sample. Apart from applying more setback during night and when away during the day, they adopt quite similar setpoint and setback temperatures as the total sample. These detached dwellings prove to have larger floor areas than the total sample. This is as expected, because the total sample also contains flats and terraced dwellings, which typically are smaller in size (see also large Spearman's rank correlation coefficient of ρ = -0.65 between TYPEBUI and FLOORM2 in Table 3.16). Overall, the energy efficiency of these subgroup dwellings proves to be somewhat lower than the total sample: (i) higher occurrences of having no insulation in roof, floor or wall, (ii) if roof insulation is present, it comes at lower thicknesses, (iii) higher occurrence of single glazing and (iv) a more outdated heating system.

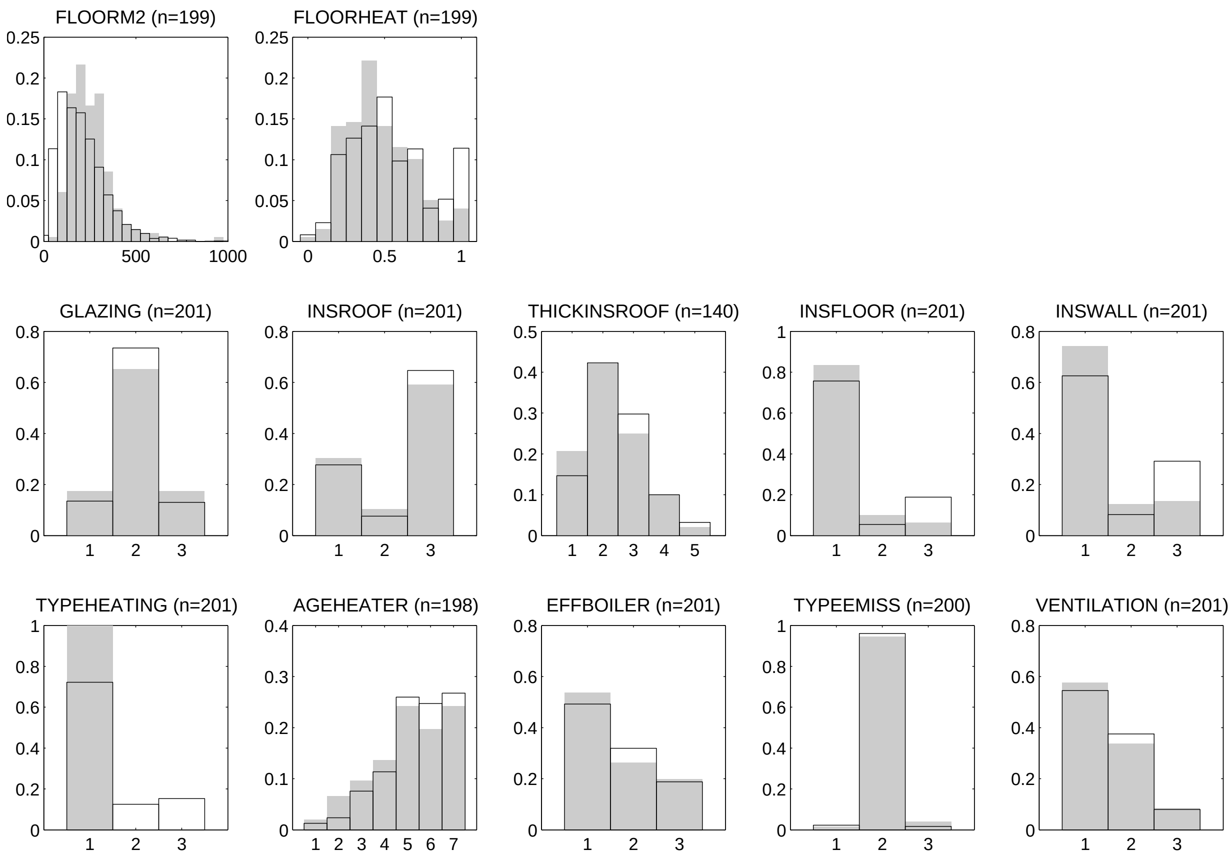


Figure 6.5: Empirical frequency distribution of the building characteristics for the subgroup (detached dwelling, built 1946-1970) in the ECS-database. Grey filled: subgroup sample - black lines: total sample. For the explanation of the x-axis: see Table 3.15.

Spearman's rank correlation coefficients

The Spearman's rank correlation coefficients for the subgroup are given in Table 6.2. Due to the smaller sample size with respect to the total ECS-sample, also the less strict significance levels α = 0.01 and α = 0.05 are shown.

Overall, and apart from the fact that less statistically significant correlations are detected in the subgroup sample, the detected ones are comparable to those of the total sample. The household characteristics are stronger correlated to each other and to the parameter WHENSETBACK (for instance, the correlation between WHENSETBACK and activity level increased from -0.13 to -0.27, pointing out how, the older the head of the household, the more often setback is applied). The building parameters are similarly correlated to each other as in the total sample, yet somewhat weaker (the correlation between the presence of roof insulation and the glazing type decreases from +0.24 to +0.16).

Table 6.2: Spearman's rank correlation coefficients between variable i and j for the subgroup of detached dwellings built between 1947-1970 - sample size different for every coefficient and depending on available answers per set of two variables.
(*) = p-value > 0.05 (correlation coefficient not significantly different from zero at the α = 0.05 level)
(bold) = p-value ≤ 0.001
(normal) = 0.001 < p-value ≤ 0.01
(italic) = 0.01 < p-value ≤ 0.05
(grey box) = correlation coefficient ≥ 0.20

	NUMOCC	NUMKIDS	AGECAT	INCOME	ACTIVITY	TSETPOINT	WHENSETBACK	DELTAT	FLOORM2	%FLOORHEAT	GLAZING	INSROOF	THICKINSROOF	INSFLOOR	INSWALL	AGECATHEATER	EFFBOILER	TYPEEMISS	VENTILATION
NUMOCC	1	**0.64**	**-0.55**	**0.58**	**0.51**	*	*0.15*	*	*	0.18	*0.16*	*	*	0.21	*	*	*	*	*
NUMKIDS		1	**-0.56**	**0.46**	**0.47**	*	0.22	*	*	0.19	*	*	*	*0.16*	*	*	*	*	*
AGECAT			1	**-0.53**	**-0.83**	*	**-0.27**	*	*	*-0.17*	-0.21	*	*	-0.23	*-0.15*	*	*	*	*
INCOME				1	**0.54**	*	0.19	*	*0.15*	**0.24**	**0.25**	*	*	**0.26**	*	*	*	*	*0.14*
ACTIVITY					1	*	**0.26**	*	*	*0.17*	0.2	*	*	**0.23**	*	*	*	*	*
TSETPOINT						1	*	**0.43**	*	*	*	*	*	*	*	*	*	*	*
WHENSETBACK							1	*	*	*	*0.15*	*	*	*	*	*	*	*	*
DELTAT								1	*	*	*	*	*	*	*	*-0.15*	*	*	*
FLOORM2									1	**-0.35**	*	*	*	*	*	*	*	*	*
%FLOORHEAT										1	*0.16*	*	*	*	*	*	*	*	*
GLAZING											1	*0.16*	*0.19*	0.21	0.19	**0.24**	0.19	*	*
INSROOF												1	*	*	**0.29**	*0.15*	0.19	*	*
THICKINSROOF													1	*	*	*	*	*	*
INSFLOOR														1	**0.27**	*	*	*	*0.18*
INSWALL															1	0.22	**0.23**	*	*
AGECATHEATER																1	**0.63**	*	*
EFFBOILER																	1	*-0.17*	*
TYPEEMISS																		1	*
VENTILATION																			1

6.3.2 Composing the dwellings

Three different ways are investigated to capture the wide variety in building characteristics of the 201 dwellings.

The first option is the aforementioned *sample* technique: the ECS-subgroup of 201 households represent a sample taken from the total population of dwellings in open typology built between 1946-1970. The 201 dwellings are then modelled following the survey information and the behavioural model is imposed to each of them. As it stays closest to the available information of the subgroup, this option is believed to approximate best the actual situation. Through its description (following hereunder), the composition of the hypothetical subgroup housing stock is elucidated.

The second option is the aforementioned *archetype* technique: only one single dwelling is composed, believed to be representative for the entire subgroup, and the behavioural model is imposed. To account for differences in modeller's judgements, two possible archetypes are considered.

The third option is the so-called *stochastic* technique: the dwellings are not predefined, but instead only characterized by the empirical probability distributions of the ECS-subgroup and its correlation coefficients. Hence, multiple Monte-Carlo simulations are performed, sampling both user behaviour and dwelling characteristics simultaneously.

Sample technique

In order to construct each of the 201 dwellings of the sample, and apart from the Lijsterlaan geometry, the following additional information is needed and constructed as follows (for variables 4→9 the parameters in capital refer to the corresponding parameter of the ECS-database):

(1) *orientation front facade*
Sampled from discrete uniform distribution U(0,359) °.

(2) *depth of the extension*
Sampled from uniform distribution U(0,3) m.

(3) *air permeability n_{50}*
Sampled from lognormal fit on the measurement data of the Lijsterlaan dwellings, as shown in Figure 6.6, yet with a cut-off at 20 h^{-1} to avoid unrealistically high values.

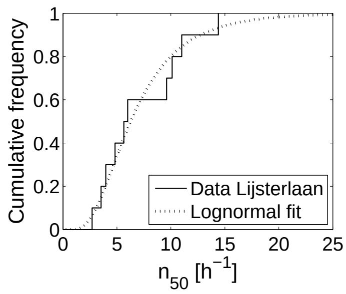


Figure 6.6: Air permeabilities as measured on the Lijsterlaan dwellings (see also Table 4.4)

(4) *insulation thickness roof*
Whenever roof insulation is said to be present (DINSROOF = 2 or 3), all roofs are insulated with the same insulation thickness of mineral wool (λ_{MW} = 0.041 W/(mK)). The thickness is randomly sampled from within the insulation thickness range of THICKINSROOF (1-5cm, 5-10cm, etc.).

(5) *insulation thickness wall*
Whenever wall insulation is said to be present (DINSWALL = 2 or 3), a 6 cm insulation thickness of PUR (polyurethane - λ_{PUR} = 0.028 W/(mK)) is applied in all walls.

(6) *insulation thickness floor*
Whenever floor insulation is said to be present (DINSFLOOR = 2 or 3), a 6 cm insulation thickness of PUR (λ_{PUR} = 0.028 W/(mK)) is applied in all floors.

(7) *glazing type*
The three classes of GLAZING are translated into the following $U_{glazing}$-values [W/(m^{2}K)]: *'single glazing'* → U = 5.86, *'double glazing'* → U = 2.83, *'high efficiency/triple glazing'* → U = 1.06

(8) *ventilation system*
The three classes of VENTILATION are translated as follows: *'no ventilation system'* → no ventilation air flows, *'trickle ventilators'* → system A, *'mechanical exhaust w/o heat recovery'* → system D with heat recovery

(9) *heating system efficiency*
The three classes of EFFBOILER are translated as follows: *'no high efficiency label'* → $\eta_{overall,heat}$ = 0.65, *'2/3 high efficiency/condensing label'* → $\eta_{overall,heat}$ following Figure 4.8.

For the variables 1→3 a Latin-Hypercube space-filling sampling scheme of 3 parameters in 201 runs is generated; for all other variables the corresponding survey value is taken from each of the respective 201 households. The behavioural model is then imposed to every sample dwelling in a sampling scheme of 75 runs and 13 behavioural parameters. Only 75 runs (compared to the 200 runs when also the 10th and 90th percentile are to be estimated reliably - see Figure 5.4) are adopted here to keep total simulation time manageable (201 dwellings × 75 runs already takes about 4 days computation time on a 2.53 GHz Intel(R) Core(TM)2 Duo processor). The feasibility of reducing the amount of runs for the sample technique will be investigated in 6.3.4. Interestingly, when averaging the 75 runs per dwelling, 201 dwelling mean values are obtained in which the user behaviour variability is eliminated −these 201 values thus only represent the dwelling variability of the subgroup and will also be shown in the comparison of all techniques.

Archetype technique

A 'best guess' archetype dwelling is composed by averaging the variables 1→3 from the sample dwellings −see Table 6.3. For all other variables, the most likely values −considered to be the best guesses a modeller can make, given the available information− are taken over from Figure 6.5. Note that by doing so this best guess dwelling is already remarkably more representative for the subgroup's insulation level than if one would be solely relying on the construction period. The latter would imply a totally uninsulated dwelling with single glazing (as is done e.g. in Hens et al. (2001), Dooms et al. (2008), Cyx et al. (2011)) which is a very pessimistic estimation of the actual situation.

Table 6.3: Characteristics of the archetype dwellings

		'Best guess'	'Average'
(1)	orientation front facade	184 ° (~ North)	
(2)	depth extension	1.51 m	
(3)	n_{50}	7.30 h^{-1}	
(4)	insulation thickness ROOF	0.08 m	0.026 m[a]
(5)	insulation thickness WALL	0 m	0.005 m[a]
(6)	insulation thickness FLOOR	0 m	0.004 m[a]
7)	glazing type	double glazing	(3 types)
	→ U_m	1.15 W/(m^2K)	1.18 W/(m^2K)
(8)	ventilation system	no ventilation system	(3 systems)
(9)	boiler characteristics	no high efficiency label	(3 boilers)

[a] Determined by requiring that $U_{ROOF/WALL/FLOOR,archetype}$ == $U_{ROOF/WALL/FLOOR,sampleAveraged}$

The above working method implicitly assumes that taking over the most likely values will also lead to the most likely energy use prediction. This is of course not necessarily true. Therefore, a more evidence-based approach is also investigated, in which an 'average' archetype dwelling is composed by rigorously averageing all dwelling parameters from the sample dwellings, as is done in Deurinck et al. (2014). For the geometric characteristics (like the extension depth), infiltration rates and U-values of the opaque building envelope elements this is a quite straightforward procedure −see Table 6.3. However, the 3 glazing types cannot be averaged, because they make up discrete components in the TRNSYS simulation environment. Nor can the 3 ventilation systems be averaged: while it could make sense to average the ventilation rates (n_{vent}), there is no physical meaning in averaging a heat recovery efficiency over dwellings who do not own one. The same can be argued for the efficiency of the 3 boiler types. To solve this, 3 × 3 × 3 = 27 subvariants of the same archetype dwelling are run and their output is weighted averaged following the occurring combinations of the glazing type, ventilation system and boiler within the sample dwellings. This is of course an unwieldy task and one might argue about the relevance and feasibility of this in a transparent, easily adaptable housing stock model. Nevertheless, this option is retained in the current analysis, as it does offer a reasonable and useful estimate of the mean energy use of the subgroup considered (see further).

The behavioural model is imposed to every archetype dwelling in a Latin-Hypercube space-filling sampling scheme of 13 behavioural parameters in 200 runs, a sample size which has proven to reliably estimate not only the mean value of the energy use for space heating but also the extents of the probability distribution (see 5.2.2).

Stochastic technique

This technique is rather straightforward. n stochastic dwellings with respective user are composed by generating a Latin-Hypercube space-filling sampling scheme of 13 behavioural + 10 building parameters (1→9 + THICKINSROOF)= 23 parameters in n runs. A large sample size of n = 3000 runs is chosen as baseline. Due to this large sample size the output can be considered sampling scheme independent, which is a prerequisite to assess the intrinsic capability of the stochastic technique to capture the dwelling variability −independently of the sampling size and scheme chosen. The feasibility of reducing the 3000 runs to a more practical amount of runs will be investigated in 6.3.4.

The building parameters 4→9 from above are now sampled from the subgroup distributions shown in Figure 6.5. Also, the correlation matrix of the behavioural model is extended with the building-related correlations of the subgroup sample for the variables GLAZING, INSROOF, THICKINSROOF, INSWALL, INSFLOOR, EFFBOILER and VENTILATION of Table 6.2.

6.3.3 Comparing the different techniques

By lack of actual measurement data and due to hypothetical set-up of the subgroup considered, it is of course impossible to make statements about the 'correctness' of either of the above techniques. Nevertheless, inter-comparison is still possible. The *sample* technique is believed to stay closest to the actual variety of building parameters and can act as the reference situation against which the two other techniques can be compared.

In the following, three aspects are considered: the dwelling mean U-value U_m, energy use for space heating and energy savings in case of a minor and a major retrofit.

Dwelling mean U-value U_m

In Table 6.4 and Figure 6.7 the average value and the cumulative distribution function of the dwelling mean U-value are shown respectively.

Table 6.4: Average value of the dwelling mean U-value U_m

	U_m [W/(m^{2}K)]
201 sample	1.18
"best guess" archetype	1.15
"average" archetype	1.18
3000 stochastic uncorrelated	1.18
3000 stochastic correlated	1.19

From Table 6.4 it is immediately clear how both the archetype and the stochastic technique are very well able to catch the mean U-value of the subgroup. For the "average" archetype, this is of course as expected as it was designed to match to the individual building envelope U-values. In Figure 6.7 it is demonstrated how the stochastic technique performs reasonably well in matching the probability distribution of the sample dwellings, with the correlated technique outperforming the uncorrelated one. Even when correlated though, the spread of the stochastic technique remains somewhat smaller (underestimation of tails from the sample technique).

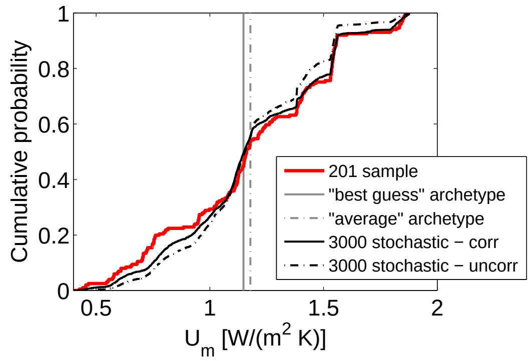


Figure 6.7: Cumulative probability distribution of the dwelling mean U-value of all dwellings '1946-1970 open typology'.

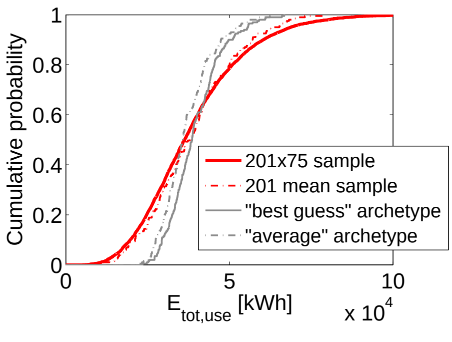
Energy use for space heating

Table 6.5 summarizes the mean energy use for space heating. It is clear how both the archetype and stochastic technique are very well able to estimate the average energy use; the relative differences with the sampling technique are small and certainly in the acceptable range for a housing stock estimate.

Table 6.5: Average value of the total energy use for space heating $E_{tot,use}$ [kWh].

	$E_{tot,use}$ [kWh]
201 sample	38532
"best guess" archetype	+ 2.5 %
"average" archetype	- 4.0 %
3000 stochastic - corr	- 0.4 %
3000 stochastic - uncorr	- 0.6 %

In Figure 6.8 the corresponding probability distributions are shown. Concerning the sample technique (Figure 6.8a), two curves are shown: one containing all values of the 75 users in each of the 201 dwellings ("201x75 sample") and one containing only the 201 dwelling mean energy uses ("201 mean sample"). The spread of the latter curve is only due to the dwelling variability in the sample and is, as expected, smaller than the one containing all values. However, the difference is limited, so –at least for the current situation of an already large variability within the subbgroup– the



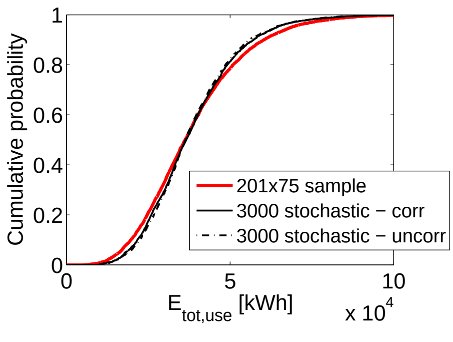


Figure 6.8: Cumulative probability distribution of the energy use for space heating for the dwellings '1946-1970 open typology': comparison of sample technique with (a) archetype technique and (b) stochastic technique.

user behaviour does not induce many additional variability. Conversely, the cumulative curve of the archetypes is only due to the user behaviour. The spread is now smaller, yet certainly not negligible. Compared to the above U_m ranking ($U_{m,bestGuess}$ < $U_{m,Average}$), both archetypes switch position concerning the energy use ($E_{tot,use,bestGuess}$ > $E_{tot,use,Average}$), due to the "best guess" archetype having no high-efficiency boiler.

The stochastic technique (Figure 6.8b) clearly approximates the sampling technique best. Quite as expected from the smaller spread in U_m-values, the energy use curve is somewhat steeper than the one of the sampling technique, but the difference is limited. Also, the aforementioned difference between correlated and uncorrelated dwellings is no longer pronounced.

Energy savings

Similarly as in 5.5, a major and a minor retrofit are considered:

- a 'minor' retrofit in which all roofs (pitched, flat and ceiling towards the unheated attic) are insulated to a mineral wool thickness of 0.25 m, and
- a 'major' retrofit in which also the walls and the floors are insulated to an insulation thickness of 0.06 m PUR and 0.10 m PUR respectively, all windows are replaced by highly insulating glazing (U = 1.06 W/(m^{2}K); g-value = 0.59) in wooden profiles, the air permeability is assumed to drop to n_{50} = 1 h^{-1}, all boilers are replaced by condensing gas boilers and a balanced ventilation system with a heat recovery unit is installed.

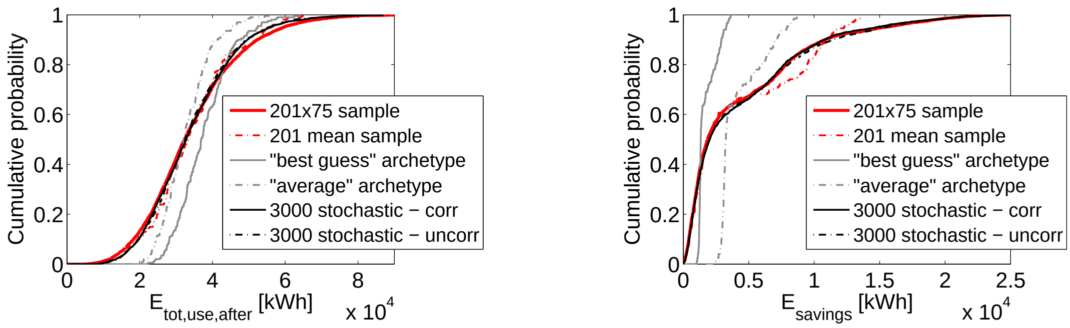
When the major retrofit is imposed, the dwelling variability is strongly reduced; the dwellings only differ in orientation and volume (via depth of extensions). Consequently, there is no more need to run several variants for the "average" archetype to account for the different discrete subcomponents (glazing type, ventilation and heating); the archetypes "best guess" and "average" coincide.

Table 6.6 gives the average values for the energy uses after retrofit and the resulting energy savings. Figure 6.9 and 6.10 show the corresponding cumulative probability distributions.

Concerning the roof insulation of the *minor* retrofit, two effects are important when interpreting the energy saving curves of Figure 6.9b: (i) whether or not the nightzone is heated and (ii) whether or not the dwelling already had roof insulation before retrofit. Both effects are mixed up in the total distribution curve of the sampling technique (full red line), while the effect of the initial roof insulation

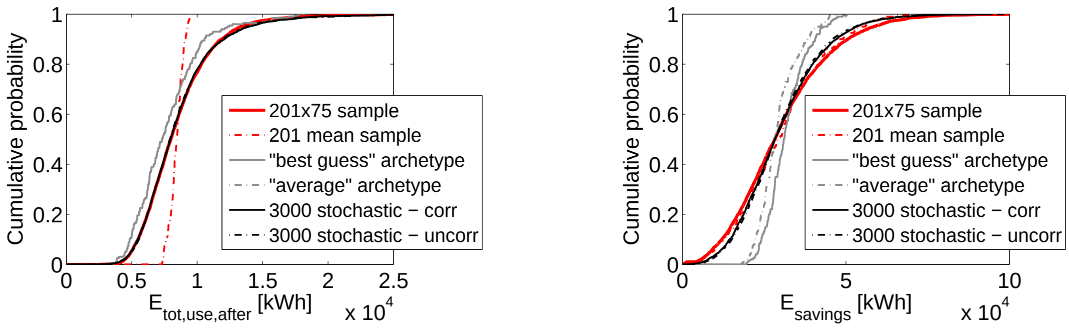
Table 6.6: Average value of the total energy use for space heating after retrofit and the resulting energy savings.

	MINOR RETROFIT		MAJOR RETROFIT	
	$E_{tot,use,after}$ [kWh]	$E_{savings}$ [kWh]	$E_{tot,use,after}$ [kWh]	$E_{savings}$ [kWh]
201 sample	34252	4280	8446	30086
"best guess" archetype	+ 10.2 %	- 59.4 %	- 8.6 %	+ 5.6 %
"average" archetype	- 4.2 %	- 1.9 %	- 8.6 %	- 2.7 %
3000 stochastic - corr	- 0.6 %	+ 0.9 %	- 0.6 %	- 0.7 %
3000 stochastic - uncorr	- 1.0 %	+ 2.9 %	+ 0.4 %	- 0.9 %



(a) (b)

Figure 6.9: MINOR RETROFIT: Cumulative probability distributions for the dwellings '1946-1970 open typology': (a) energy use for space heating and (b) resulting savings.



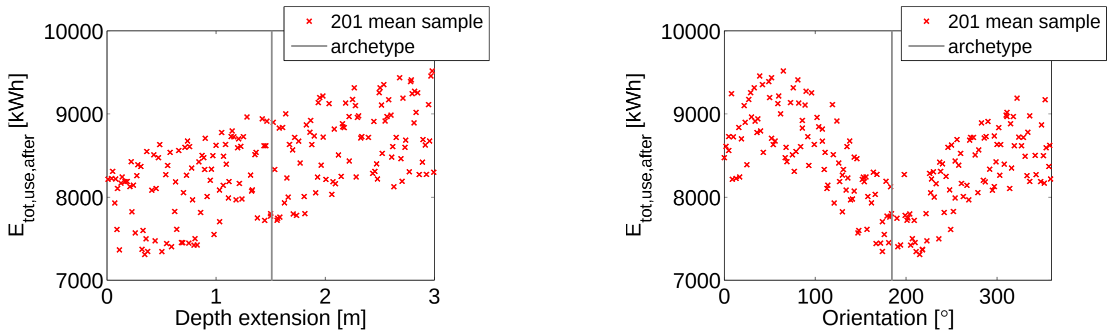
(a) (b)

Figure 6.10: MAJOR RETROFIT: Cumulative probability distributions for the dwellings '1946-1970 open typology': (a) energy use for space heating and (b) resulting savings.

is isolated when averageing out the user behaviour (dashed red line). Within the latter, a shiftpoint is visible around 0.7, dividing the dwellings with and without initial roof insulation. When user behaviour is added (full red line), the influence of heating the nightzone pushes the right tail of the distribution curve to more extreme values. All this is very well captured by the stochastic technique. Again, there is no relevant difference between the correlated or uncorrelated stochastic dwellings.

The situation is different for the archetype dwellings. As they only capture the user behaviour, their distributions experience much less spread and exhibit a different shiftpoint, dividing the 60 % of users who never heat the nightzone (steep part) from those who do (flatter part). Despite the strong difference in curve though, the "average" archetype dwelling offers a reasonable estimate of the mean energy savings (see Table 6.6). The "best guess" dwelling does not, as it is assumed to have already 8 cm roof insulation before retrofit, leading to a large underestimation of the energy saving potential.

Concerning the *major* retrofit, the energy savings are predicted following the sample technique to be 78 % of the initial energy use, making the energy saving curves almost equal to the initial energy use curves of Figure 6.8. When looking at the energy use after the major retrofit (Figure 6.11a), the dashed red line again only represents the dwelling variability, which is as expected very limited (only orientation and depth of extension). Conversely, the archetype curve only represents the user behaviour variability. This variability is now predominant –as can be expected in a well insulated dwelling– and is similarly detected in the sample and stochastic technique. Despite the archetype dwelling being almost equal to all other dwellings after the major retrofit, it predicts a significantly lower energy use. This highlights the dependence of the well insulated dwelling of the two remaining variables, orientation and volume –see Figure 6.11: for this case the orientation of the archetype dwelling is clearly associated to the lowest energy uses.



(a) *(b)*

Figure 6.11: MAJOR RETROFIT: Energy use for space heating after retrofit (dwelling mean values of the sample technique) as a function of (a) depth of extension and (b) orientation of front facade.

6.3.4 Reducing the computation time for stochastic and sample technique

To enable a robust investigation of the stochastic technique it was necessary to rely on a large sample size (3000 runs). Also for the sample technique, each of the 201 dwellings had to be run 75 times to account for the user behaviour, leading to an unpractically long calculation time. When using either of these techniques in an actual bottom-up housing stock model, the computation time is preferably reduced as much as possible, whilst still retaining the overall reliability of the generated output. The feasibility of doing so is investigated here, for the sample and stochastic technique respectively.

It must be stressed that the following reduced sample sizes are meant to give a global indication of practically feasible sample sizes, deduced specifically within the framework of the present analysis and not to be extrapolated to other subgroups of the Belgian housing stock nor to other building energy simulation applications. For instance, subgroups demonstrating more/less dwelling variability are expected to require larger/smaller sample sizes respectively. Moreover, while a reduced sample size could be well suitable to assess the overall energy use output of the total sample considered, this is no longer the case when deducing and analysing specific subgroups within that overall output. If for instance the stochastic technique is run only 200 times for the aforementioned subgroup and one wants to further analyse in detail those dwellings with mean U-values smaller than, say, 1 W/(m^{2}K), only about 50 of those dwellings, and consequently only 50 users, are retained. It is not feasible to draw reliable conclusions from this limited subgroup, because it is possible that important variability, spread over the remaining 150 values, is missed. In order to solve this, a multi-layered sampling scheme would be needed (Van Gelder 2014), ensuring that all dwelling and user behaviour parameters are fully employed within the subgroup desired, thereby of course increasing the amount of runs.

Sample technique

In order to include the user behaviour variability, each of the 201 sample dwellings has been run 75 times (which already meant a reduction of the initial 200 runs). An alternative is available however by taking over the working method of the stochastic technique: instead of imposing the whole range of user variability to every dwelling separately, the user behaviour variability is distributed across the sample dwellings. This is done by generating 201 stochastic user profiles and imposing the 1^{th} profile in the 1^{th} dwelling, the 2^{nd} profile in the 2^{nd} dwelling, etc. In Figure 6.12 the comparison is shown between the original output from the sample technique (201 X 75 = 15 075 runs) and the output for 3 different sets of 201 users. For all 3 sets the agreement with the original sample technique output is excellent: the probability distributions are well captured and the differences with the mean values of the original sample techniques are very small (on average in the range of 0.5-1 %). The excellent agreement could be expected: the (large) dwelling variability is automatically captured as it is by default represented in all 201 sample dwellings and their number of 201 is −by coincidence− in agreement with the deduced 200 runs necessary to capture the user behaviour variability (see 5.2.2). It is evident that if less sample dwellings would be available, the above procedure might have to be repeated several times with different user profiles to obtain convergence.

Given these 3 basic sets it is easily investigated to what extent the agreement improves when repeating the above procedure with a different set of users profiles, as such covering 2x201 = 402 users. To do so, 3 combinations can be made, extracting 2 sets out of the 3 basic sets. The results are shown in Figure 6.13, demonstrating that the probability distribution curves are now captured very well, while the relative differences with the mean values do not further decrease.

Stochastic technique

For the stochastic technique 3 different Latin-Hypercube space-filling sampling schemes are generated, once for 200 and once for 500 runs. The comparison with the original output of 3000 runs is shown for the 200 and 500 runs in Figure 6.14 and 6.15 respectively. A sample size of 200 runs already yields satisfactory results: the probability distributions curves are catched nicely and the relative differences with the mean value are in the range of only 0-2.5 %. Significantly larger errors are made (up to 12 %) regarding the energy savings of the minor retrofit, demonstrating how the large spread for that specific retrofit measure (whether or not a dwelling already has roof insulated can be heavily magnified by whether or not it is combined with users who heat the nightzone) needs a higher amount of runs to be fully captured. When looking at the results of the 500 runs, the probability distribution curves are now clearly matching better those of the reference output and the maximum observed error in predicting the minor retrofit energy savings is now only 5 %.

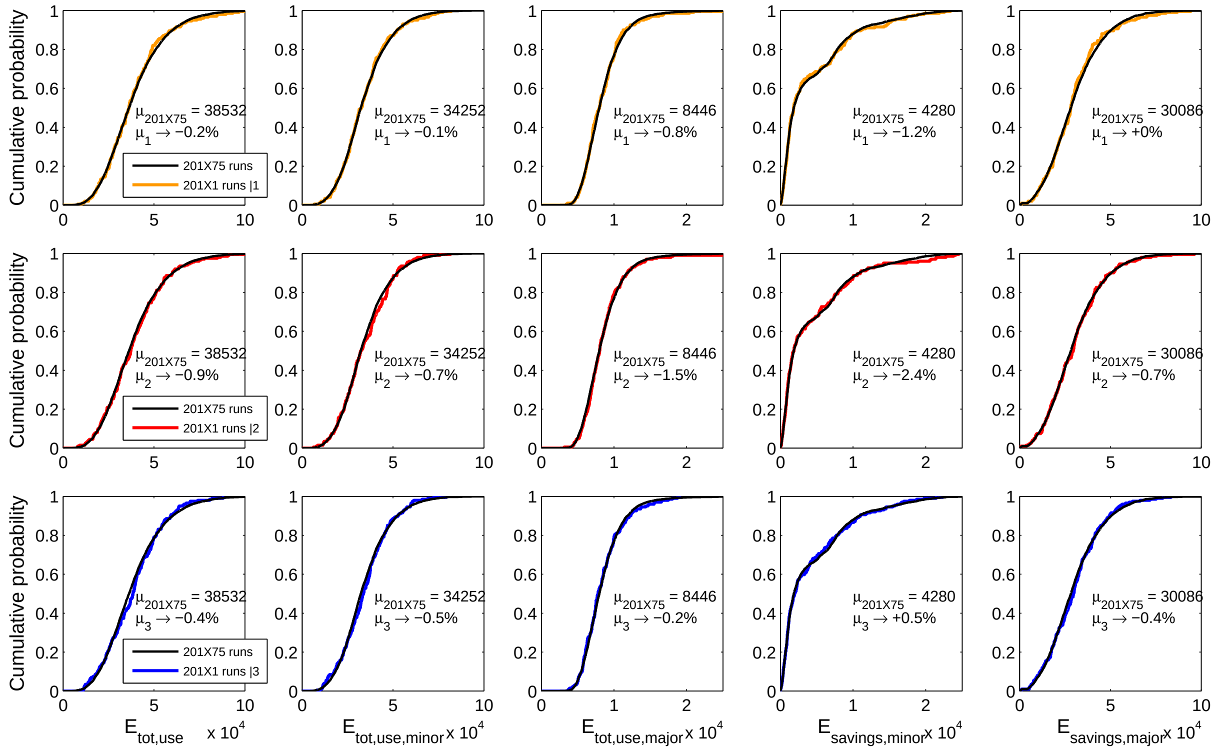


*Figure 6.12: Cumulative probability distributions of the energy uses for space heating and resulting energy savings, all in [kWh]: comparison for the **sample technique** between the 201 X 75 runs and 3 different Latin-Hypercube space-filling schemes of only 201 runs (201 users are distributed across the 201 dwellings)*

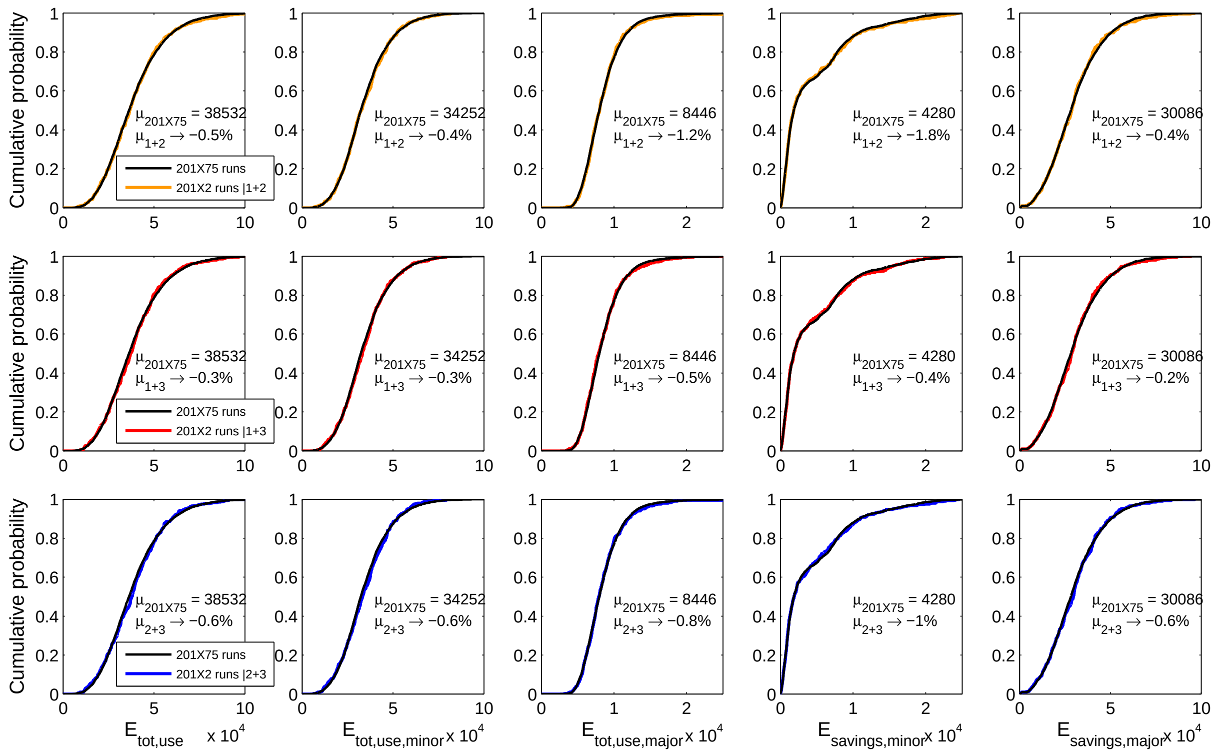


*Figure 6.13: Cumulative probability distributions of the energy uses for space heating and resulting energy savings, all in [kWh]: comparison for the **sample technique** between the 201 X 75 runs and the combinations of 2 out of the 3 basic sets from Figure 6.12, representing 201X2 runs (every dwelling is computed twice).*

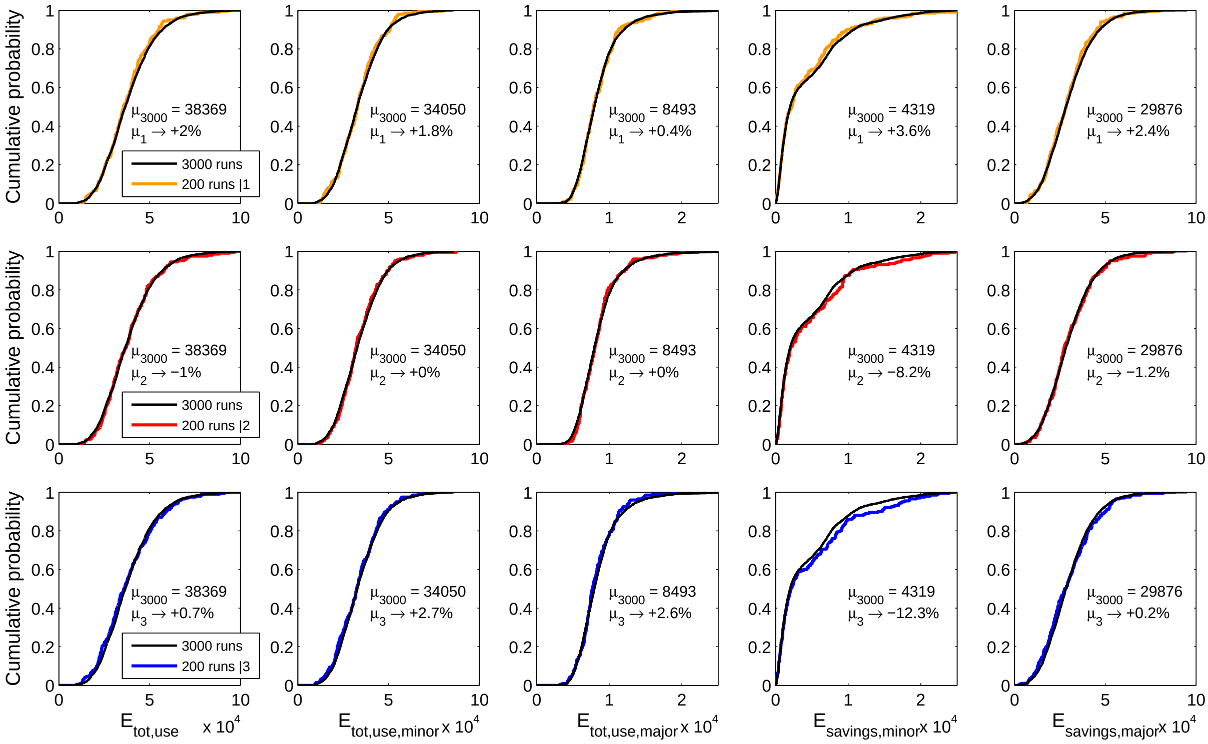


*Figure 6.14: Cumulative probability distributions of the energy uses for space heating and resulting energy savings, all in [kWh]: comparison for the **stochastic technique** between the 3000 runs and 3 different Latin-Hypercube space-filling schemes of 200 runs.*

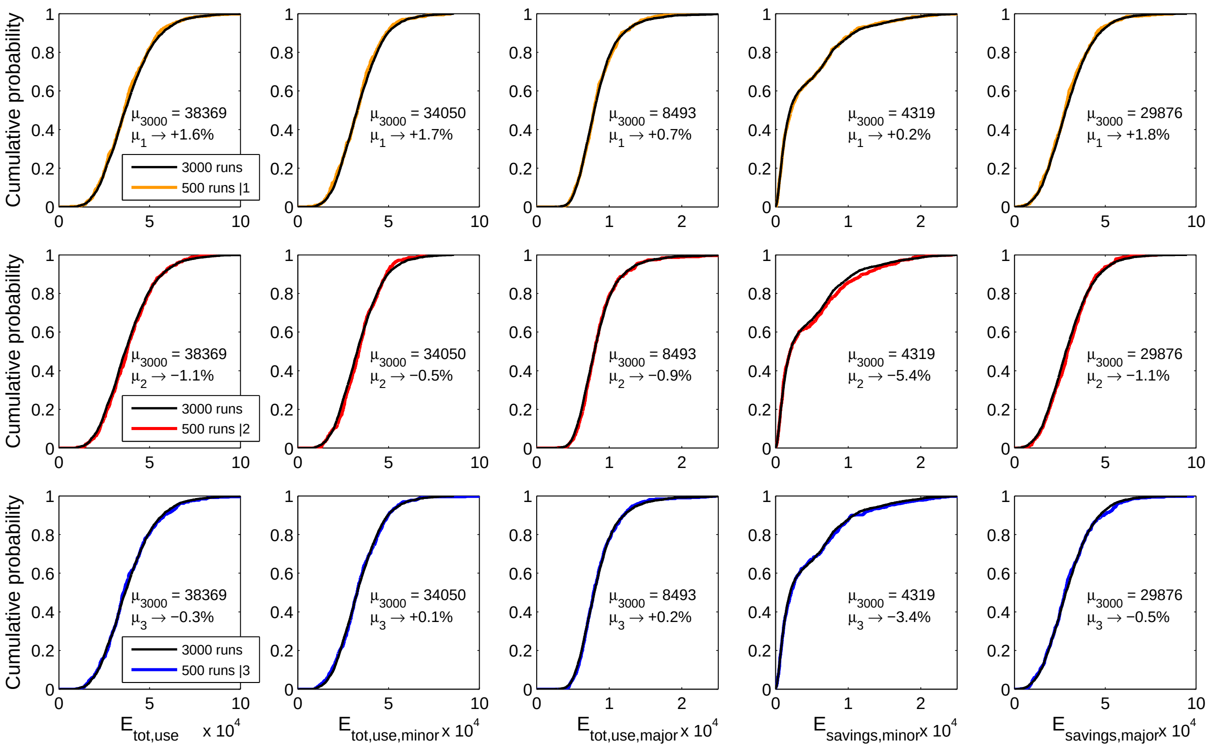


*Figure 6.15: Cumulative probability distributions of the energy uses for space heating and resulting energy savings, all in [kWh]: comparison for the **stochastic technique** between the 3000 runs and 3 different Latin-Hypercube space-filling schemes of 500 runs.*

Overall, good confidence is obtained that both the sample and stochastic technique are capable to be reliably applied in a housing stock model with a significantly smaller and feasible amount of runs. A small sample size of 200 runs already yield satisfactory results for the current application −only for the stochastic technique a higher amount of runs is needed to reliably predict the energy savings of the minor retrofit.

6.3.5 Discussion

All three techniques have been evaluated on a 'fair' basis: they could all rely on the same, rather rich dataset available in the ECS-database. By doing so, their ability to capture the same dwelling variability can be compared −independently of possible drawbacks that often occur in reality. For example, it was possible here to compose the archetype dwelling as close to the sample technique as possible. In reality however, the archetype technique is typically chosen when detailed (survey) data is scarce, so additional errors are easily made.

The above analysis makes clear how, if all techniques can rely on the same rich dataset and if one is only interested in the average estimates, all techniques −apart from the "best guess" archetype− perform almost equally well. If one is also interested in the distribution of those energy savings over the subgroup the stochastic and sample technique are definitely preferred.

There is also another reason why these two are preferred: the large variability in building characteristics can be incorporated more easily and in a more building physics based way. Certainly for individual retrofit measures like the roof insulation, the archetype technique can only predict reliable output if it has been rigorously composed to match the subgroup's average values. This proved to be a rather unwieldy task, especially because not only building envelope parameters are to be averaged, but also discrete systems like heating or ventilation components, requiring additional variants to be weighted averaged afterwards. Such procedure of course hampers an easy implementation within a housing stock model and the link with actual building physics processes is easily lost. If in contrast one chooses to compose an archetype dwelling based on the most likely values, expert judgements or (default) assumptions, the output is very sensitive to these values and risk is high that the energy savings are a severe over- or underestimation of actual energy use/savings.

By investigating the feasibility to reduce the amount of simulations it is shown how both the sample and stochastic technique are able to produce reliable output with a relatively small amount of simulations, making both suitable for practical use in a bottom-up housing stock framework. Two aspects in favor of the stochastic technique must be highlighted though.

Firstly, in contrast to the sample technique, the stochastic technique allows to combine different databases. As it is based on probability distributions (and optionally correlation coefficients), one does not need to rely on one single large-scale survey campaign, having obtained all possible input parameters for the building energy simulation for every dwelling (and geometry, and insulation level, and heating system properties etc.), but one can rely on different and aggregated data sources of different levels of detail. Typically these kind of data sources are already available and collected for use in the more traditional archetype technique, implying that relatively little additional effort needs to be done to set up a stochastic −instead of deterministic− characterization of the housing stock.

Secondly, the stochastic technique has the intrinsic option to link the inhabitant with the dwelling characteristics by completing the right upper-part of the correlation matrix −see Figure 6.16. The sample technique cannot do so, because the predefined building parameters cannot be part of a sampling scheme in which the influence of the correlation matrix is included. The ECS-database for instance revealed how larger households live more in detached dwellings with larger floor areas, and how higher incomes are associated more with detached dwellings, larger floor areas and higher chance that insulation of any kind is present. In the current situation, the added value of doing so is however expected to be small: (i) the correlation coefficients as detected in the ECS-database are low and only link the household characteristics (not strongly influencing the heating behaviour) with dwelling parameters, and (ii) some heating behaviour parameters that strongly influence the energy use for space heating are not included (heating behaviour in the nightzone, window opening behaviour). Evidence for the small impact is observed in the fact that the energy uses for space heating between a correlated and uncorrelated behavioural model (Figure 3.22) or correlated and uncorrelated stochastic dwellings (see above) were very similar.

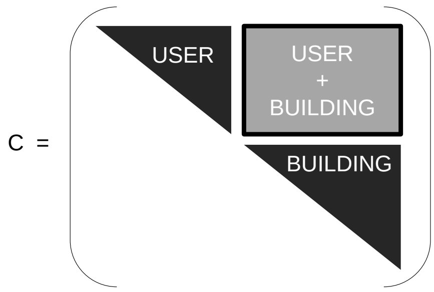


Figure 6.16: Possible extension of stochastic technique: link user with building characteristics by completing right upperpart of correlation matrix.

Of course, further improvements to all techniques are possible and needed. For instance, uncertainty about the actual performance of the retrofit measure can be included by making the target parameters stochastic (e.g. expected production efficiency of new boiler as probability distribution); retrofit application degrees can be encompassed, accounting for the fact that for example exterior insulation is not possible in a certain fraction of houses (due to e.g. historical facade); additional geometries (1/2/3 storeys, different width over length ratio, etc.) can be constructed and appended to better capture the actual dwelling variability of the subgroup considered.

When the presented application at subgroup level is scaled up towards the total national housing stock, the stochastic technique could be applied for separate subgroups and the subgroup outputs could then be combined to assess the housing stock estimate. Within this working method, every subgroup can have his own input distributions, not only concerning the dwelling characteristics, but also concerning the behavioural parameters. Additionally however, it would be worthwhile to investigate if the division in subgroups could not be avoided by running only one single loop across the housing stock, sampling all dwellings and users simultaneously from the global housing stock distributions. The stochastic technique would be particularly suited to do so and the total computation time could be drastically reduced. Given an overall correlation matrix, like the one from the ECS-database, mutual links between household, behavioural and dwelling characteristics could be accounted for. However, a correlation coefficient cannot capture everything (e.g. U-shapes between variables), so a further in-depth analysis into how these characteristics are spread across the housing stock is needed to reveal the feasibility of this approach.

6.4 Uncertainty within bottom-up housing stock models

Though subtle and despite it being more of a methodological issue, a distinction should be made between uncertainty and variability (U.S. EPA 2011).

Variability refers to the inherent heterogeneity one has to deal with; doing more measurements cannot reduce variability, it can only lead to a better categorization. As said, in the context of housing stock models, the most apparent examples of variability are the large variation in user behaviour and the enormous heterogeneity in building forms, geometries, insulation levels, heating systems etc. Even though the extent of both might of course be unknown and uncertain (like for instance the lack of knowledge about the heating behaviour in the nightzone), this could −in theory− be solved by doing additional survey campaigns, measurements etc. leading to a (more) complete mapping of actual variability.

Uncertainty clearly refers to a lack of knowledge, due to lack of data, an incomplete understanding of the phenomena observed, a simplified modelling of reality etc. Uncertainty can −again in theory− be reduced or eliminated with more or better data, more measurements, better models etc. In housing stock models such uncertainty arises from using building energy simulation models to estimate actual energy use, from lack of knowledge about the input values for these models, from simplifying the housing stock heterogeneity by using archetype or sample technique, etc.

While the previous section focussed on capturing the intrinsic variability of the housing stock, the current section aims at demonstrating how, until nowadays, uncertainty is (not) dealt with in the context of the bottom-up housing stock models and provide a framework to assign both variability and uncertainty within the housing stock predictions.

6.4.1 Different kinds of uncertainty

Two complementary ways of describing the uncertainties within a housing stock model are discussed hereunder: (i) uncertainties at individual dwelling level versus aggregated level, and (ii) input versus modelling uncertainty.

Individual dwelling versus aggregated level

Roughly seen, uncertainty plays a role at two separate levels within a housing stock model: in a first stage at the individual dwelling level and in a second stage when upscaling the individual results to the aggregated level (city/district/regional/national). Incorporating uncertainty at the individual dwelling level is a widespread feature nowadays and as such very well documented (see, e.g., Lomas and Eppel (1992), Dyrstad Pettersen (1994), de Wit (2001), Macdonald (2002), Brohus et al. (2009)). Typical uncertainties are thermal conductivities, infiltration rates, heating system efficiencies, air change rates of ventilation systems, set-point temperatures, internal gains, ...

Uncertainty at the aggregated level is of course strongly linked to the uncertainty at individual dwelling level, but also goes beyond it (Booth et al. 2011). Now the aggregated parameters become important: how reliable is the statistical data available? which value to take as average parameter, for instance concerning the U-value of the walls of a specific subgroup? what about the uncertainty induced by simplifying the housing stock through an archetype dwelling? etc.

Input/parameter uncertainty versus modelling uncertainty

The *input/parameter* uncertainty is the one most commonly accounted for in typical sensitivity and uncertainty analysis and refers to the uncertainty about the exact value of the input parameters. Certainly when setting up a housing-stock model, a large amount of input data is always required, often based on a wide variety of information sources: statistical building stock data, field survey data, energy audit databases, but sometimes also educated guesses or expert judgements. In a retrofitting context, the list of uncertain parameters can be complemented with uncertainty about the expected workmanship quality, plausible ranges of airtightness improvement, the U-values eventually achieved, ...

The *modelling* uncertainty refers to (unknown) errors, inherent to any modelling process. Investigating this kind of uncertainty requires the time-consuming task of setting-up and comparing different modelling structures, so it is no surprise that modelling uncertainty is only rarely considered (de Wit and Augenbroe 2002). At the individual dwelling level, the use of a building energy modelling tool is a well-known example. Whatever its complexity, it has to rely on submodels, equations, regressions etc. to reflect actual physical processes, thereby inevitably forming a simplification of reality. At the aggregated level, modelling uncertainty is present in how the large housing stock is simplified to a manageable framework. The above archetype and sample technique of bottom-up engineering based housing stock models are two ways of dealing with it: the archetype technique by searching for representative homogenous subgroups within the housing stock and the sample technique by including the large variability through individual sample houses. Whatever technique chosen though, they are an approximation of reality and as such induce (modelling) uncertainty.

6.4.2 Current practice

While incorporating (mainly input) uncertainty is already widespread practice at the individual dwelling level, it is far less common to include it in a bottom-up housing stock modelling process. Most currently available bottom-up housing stock models are conceived entirely deterministic: every dwelling, either archetype or sample, is associated with only one energy use value and its output is multiplied by a fixed weight factor, resulting in a single estimate of energy use at city/district/national scale. This deterministic approach is of course in contrast with the many modelling assumptions and input uncertainties, inherent to any housing stock model. Also, it does not provide any insight in the uncertainty and overall reliability of the final estimate. What if some assumptions were to be altered, what if the housing stock composition would be slightly different from what is assumed etc.?

Only a few studies are found, recognizing the need for a probabilistic approach within housing stock modelling.

Local sensitivity analysis is performed on archetype based housing stock models in the UK (Firth et al. 2010, Cheng and Steemers 2011) and in Serbia (Kavgic et al. 2013). The sensitivity analysis is performed by imposing alterations to the input parameters of all archetypes and analysing the subsequent change in the energy use and CO_2-emission of the total housing stock. By doing so, the sensitivity indicators are to be interpreted as the change in housing stock energy use due to the change of an input parameter in all archetype dwellings simultaneously. Similarly as in 5.3, this working procedure does not make statements about the likeliness of those changes; it only gives insight in the possible consequences of estimating, for instance, the mean indoor set temperature wrong −taken equal throughout the whole building stock− by a small amount. Interestingly, Cheng and Steemers (2011) also developed predictive charts of the housing stock energy use to provide rapid estimations of the energy savings for various scenarios, combined with the (unknown/unpredictable) possibility of a change in the mean internal temperature of the living area of all dwellings of the housing stock −see Figure 6.17.

Whereas the above studies already offer valuable insights in the consequences at the housing stock level of several parameter assumptions at the dwelling level, their models still remain entirely deterministic: the housing stock energy use estimate will always be a single point estimate. Currently, only one housing stock model is found in which a probabilistic component is intrinsically embedded, allowing for a probabilistic characterisation of the output. It is called the Stochastic Urban Scale Domestic Energy Model (SUSDEM), developed by Booth et al. (2011) and applicable to the Salford area in the UK. The same author uses it in subsequent work on robust decision making for retrofit analyses on the urban scale (Booth and Choudhary 2012, 2013). Due to its promising assets it is discussed in more detail here.

At the heart of the model is a normative and simplified energy demand model based on the CEN-ISO standards and duplicated for a large sample of 6280 existing dwellings in total (subdivided in 20 subgroups). Many of the input values are adopted directly from the respective EPC (Energy

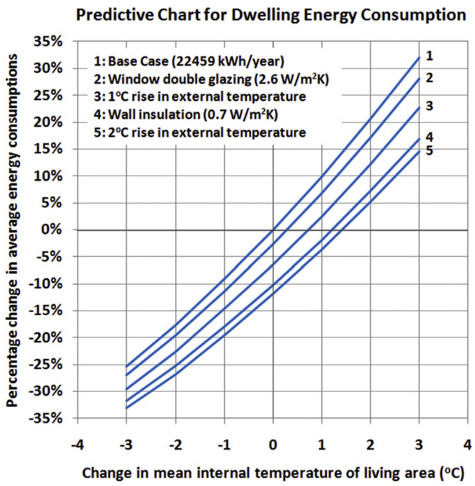


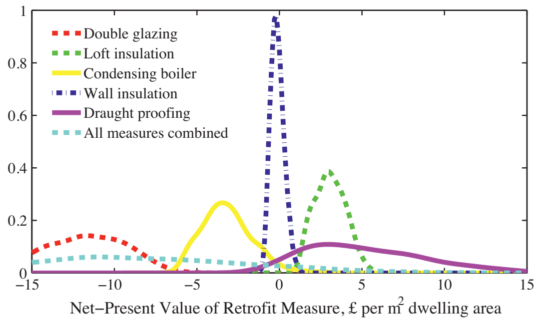
Figure 6.17: Predictive chart for averaged dwelling energy use in case of 5 different scenarios (blue line), combined with a possible, yet unknown change in the mean internal temperature of living area (x-axis). Source: Cheng and Steemers (2011)

Performance Certificate) input data, yet 6 of them are treated stochastically: the internal heating set point temperature, the fraction of space/time heated, the air leakage, overall heating system efficiency, window-to-wall ratio and double glazing U-value. Their probability distributions have been defined through Bayesian calibration on measurement data (Heo et al. 2011, Booth and Choudhary 2011). Per subgroup a stochastic output is generated through second-order Monte-Carlo simulations, consisting of two loops: (i) an *outer loop*, containing 1000 MC runs. Within every run, the input values of the 6 probabilistic parameters are sampled and imposed to all sample dwellings of the subgroup (ii) an *inner loop* (per run in the outer loop and per dwelling) to account for the 'aleatory' variation (not further specified)[2]. The final output per subgroup is then the probability distribution of the average energy use (in kWh per square meter floor area). It reflects the uncertainty range on the subgroup outcome, simply attributable to the fact that we do not exactly know the mean value of the predominant parameters of that specific subgroup. For instance, the heating set-point, taken equal for all dwellings within a subgroup, might be 20.2 °C but it might as well be 20.5 °C.

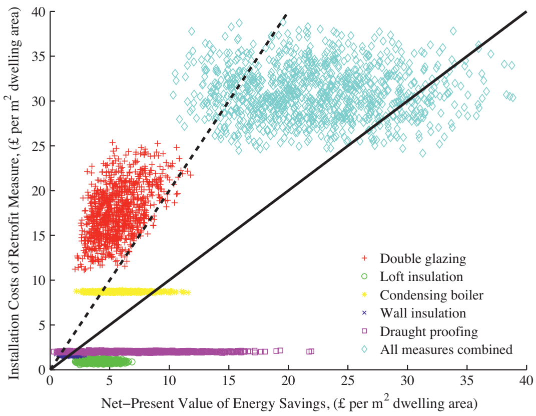
When these probabilistic results are combined with uncertain installation costs (for more details, see Booth and Choudhary (2013)), the informative graphs of Figure 6.18 are obtained. In the UK context the 'Green Deal' is set-up as a government policy, providing in finance for those retrofit measures that meet the '*golden rule*': the cost of a measure must not exceed the net present value of the expected financial savings (Booth and Choudhary 2013). The stochastic output of Figure 6.18 can seriously contribute to more robust decision making as it allows to quantify the potential risk that a measure or package of measures will fail to meet the golden rule.

As only little information could be found on how uncertainty is currently handled for in in housing

[2]The overall working method is somewhat confusing because it combines both the sample technique (different individual sample dwellings with respective EPC input values) and the archetype technique (imposing e.g. window-to-wall ratio throughout these dwellings within every MC run). Also, the added value on the final outcome of running the inner loop with 'aleatory' variation is not made clear by the authors.



(a) Probability distribution of net present value of retrofit measure (£ per m² dwelling area)



(b) Installation costs of retrofit measures (y-axis) against net present value of energy savings (x-axis), both in £ per m² dwelling area

Figure 6.18: Displaying uncertainty for robust decision making, applied to 1915-1945 semi-detached houses. Source: Booth and Choudhary (2013)

stock models, this strongly suggests how doing so is not yet widely adopted. Nevertheless, the aforementioned studies are promising and can initiate further research concerning the uncertainty propagation within housing stock energy use estimates. A proposal to do so is given hereunder.

6.4.3 Towards the inclusion of both variability and uncertainty in housing stock estimates

Variability should not only be distinguished from uncertainty from a methodological point of view, but also because both generate a different kind of output. For instance, the probabilistic output from the aforementioned stochastic technique should not be confused with the probabilistic output of the housing stock model of Booth et al. (2011), discussed previously. The probabilistic spread of Booth et al. (2011) originates from the uncertain variations in the average parameters, taken equal for all dwellings within a subgroup (e.g. the heating set-point) and represents therefore an uncertainty *around the average output of a subgroup*. The probabilistic spread of the stochastic technique originates from the inherent variations in dwelling and user behaviour parameters and only represents the variability likely to be observed *within a subgroup*. If an average output is deduced from this probabilistic output, it will eventually turn out to be a single estimate −certainly when a large number of dwellings is involved.

This is illustrated as follows. The full black line in Figure 6.8 is taken as the variability in energy use for space heating observed for a specific housing stock, being the Belgian subgroup of all dwellings '1946-1970 in open typology'. If one wants to compose the total energy use distribution for that housing stock, containing N dwellings, one could sample N values $E_{tot,use,i}$ from the distribution in Figure 6.8, sum them up to $\sum_i^N E_{tot,use,i} = E_{stock}$ and repeat this several, say 1000, times. Hence 1000 E_{stock}-values are obtained, representing the probability distribution of the total, aggregated energy use. When looking at the statistics of those 1000 values in Table 6.7, it should become clear how, for higher values of N, the spread around the mean value becomes negligibly small. Or, the total energy use might as well be calculated directly and deterministically by doing E_{stock} = N × mean($E_{tot,use,i}$).

Table 6.7: Significant reduction in the coefficient of variation, $\frac{\sigma}{\mu}$, when a larger number of dwellings is involved.

	$\frac{\sigma}{\mu}$
original distribution $E_{tot,use}$ (Figure 6.8)	0.50
resulting distribution $E_{stock} = \sum_i^N E_{tot,use,i}$ – repeated 1000 times for every N	
N = 100	0.05
N = 500	0.02
N = 1000	0.02
N = 10 000	0.01

This illustration shows how the stochastic (and also sample technique if probabilistic user behaviour is implemented) reflect the *variability within* a housing stock –as such of course providing a more reliable estimate of the total aggregated outcome– and not the *uncertainty around* the housing stock estimate. In order to quantify that uncertainty, one should question the 'hyper'-parameters of the housing stock model itself: the submodels of which it is composed, the (sometimes arbitrary) assumptions that had to be made to fill missing information, the databases on which it relies, etc. In Figure 6.19 the wider framework is given of how the uncertainty in these 'hyper'-parameters, regarding both modelling and input uncertainty, could be incorporated.

It requires the construction of two loops, (i) an *inner* loop capturing the intrinsic variability of the housing stock itself by relying on for instance the stochastic technique, and (ii) an *outer* loop, cap-

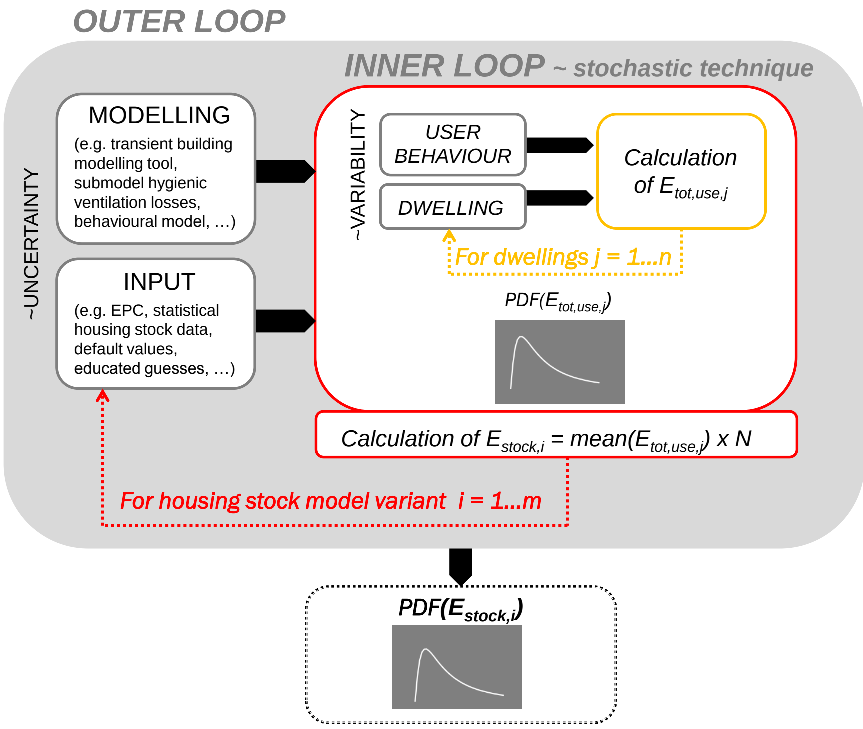


Figure 6.19: Schematic framework of how both variability and uncertainty can be incorporated within a probabilistic housing stock modelling approach.

turing the uncertainty by running that inner loop several times but with different 'hyper'-parameters of the housing stock model (submodels, assumptions, databases etc.). This procedure permits to quantify the uncertainty around the aggregated estimate, induced by the housing stock modelling process itself, and is therefore of great value when communicating the results of housing stock models towards policy makers.

6.5 Conclusion

The main focus of this chapter is put on how housing stock models deal with the large housing stock variability, reflected in the highly variable user behaviour and the large heterogeneity in dwelling characteristics. It is shown how currently two techniques exist to capture the dwelling variability: the quite straightforward and widely used archetype technique and the more data-intensive and less often used sample technique. No evidence is found for housing stock models also including the user behaviour variability.

A new technique, called the *stochastic* technique, is proposed and investigated. This technique unifies the user behaviour and dwelling variability in the probabilistic framework by including both in the same sampling scheme. Compared to the archetype technique, there is no more need for the rather unwieldy and sometimes arbitrary task of defining (representative) archetype dwellings. Compared to the sample technique, the stochastic technique is far less dependent from a large-scale and highly detailed housing databases. Instead, the currently available statistical data, typically needed for composing archetypes, can be re-used to set up the stochastic probability distributions.

An application is performed on a subgroup of the Belgian housing stock, being the detached dwellings built between 1946-1970. Information about the dwelling variability is extracted via the ECS-database. Additional assumptions –taken equal for all techniques– have been made to complete the dwelling characterizations. It is shown how the sample and stochastic technique produce almost equal estimations of the energy use and potential energy savings. The archetype technique performs differently as it is only able to reflect the user behaviour variability and as it is sensitive to the values adopted.

Finally, despite uncertainty being an intrinsic feature of bottom-up housing stock modelling, it is only rarely considered as point of attention when setting up such models, nor is there any widely spread framework about how uncertainty should be incorporated. It is pointed out how capturing the intrinsic housing stock variability leads to a more robust estimate of the total housing stock energy use, but not to an uncertainty quantification of that estimate. In order to do so the 'hyper'-parameters of the housing stock model itself should be questioned, requiring the determination of the total housing stock energy use under different, yet not necessarily less plausible submodels, assumptions, databases etc.

7

Conclusions and future perspectives

This final chapter first provides an overview of the presented work, followed by the main conclusions. Finally, the main limitations are discussed and an outlook on future research is provided.

Summary

When setting up their policies, decision makers heavily rely on bottom-up engineering based housing stock models to estimate the energy saving potential of the residential building sector. However, the overall reliability of the current housing stock models is affected by two important limitations. Firstly, the models most often rely on energy labelling tools to estimate actual residential energy use, even though the empirical evidence convincingly shows how these tools are not suited to do so. Secondly, the present housing stock models are conceived entirely deterministically, thereby neglecting the many sources of uncertainty and variability, inherent to housing stocks and their models, and as such impeding robust and informed decision making.

Hence, the overall aim of this research was to come to more reliable energy saving predictions in the residential building sector at the aggregated level. In order to do so, two research objectives were identified:

- *the development of an improved probabilistic predictive model of energy use for space heating, applicable in bottom-up housing stock models*
- *the incorporation of a probabilistic approach within a bottom-up housing stock framework*

Given these objectives and driven by the state-of-the-art, the outline of the presented work is as follows:

Probabilistic behavioural model

When aiming for a reliable representation of actual energy use in dwellings, certainly in the pre-retrofit situation, a more adequate user behaviour modelling has proven to be a key issue. This work has contributed to this by the development of a probabilistic and evidence-based behavioural model, focussing on user behaviour actions affecting the energy use for space heating.

Time-dependent *occupancy profiles* and their respective probabilities of occurrence were derived from the cluster analysis of Aerts et al. (2014) on a large-scale Belgian Time-Use Survey. Regarding the *heating preferences*, useful probabilistic data was found and implemented on the heating behaviour in the main living rooms ('dayzone'). By linking this behaviour with the occupancy profiles, real-life heating time schedules are approximated. Almost no quantitative information was found on the extent of heating in the less inhabited parts of the dwelling ('nightzone'). As such, pragmatic assumptions had to be made to fill this gap. Due to calculation time constraints and a considerable lack of empirical data, the *window opening behaviour* and *internal heat gains emission* were included in a simplified, yet stochastic way.

To incorporate the influence of so-called '*drivers*' for the individual user behaviour actions, a framework is set up within the probabilistic behavioural model, consisting of a correlated sampling technique through the use of a correlation matrix. Based on the large Belgian Energy Consumption Survey (ECS) database, a comprehensive correlation matrix was constructed. It was shown how, due to the currently low correlations and due to some important behavioural parameters missing in the database, the inclusion of the correlation matrix only limitedly influences the energy use for space heating.

A sensitivity and uncertainty analysis was carried out, revealing how the behavioural model strongly affects the energy use for space heating. In agreement with similar analyses in literature, the setpoint temperature contributes the most to the energy use variability of a dwelling, whatever its insulation level. Nevertheless, as the setpoint temperature is quite well-known and documented, it is not considered as a critical, error-inducing parameter of the behavioural model. The opposite is true for the heating behaviour in the nightzone and the window opening ventilation rates: both parameters are highly uncertain and at the same time significantly contribute to the output variability. Additional research is thus required to clarify their true extents.

Dynamic two-zone generic building model

Despite a longer calculation time per dwelling, the shift is made from the common (quasi)-steady-state calculation tools to the transient simulation environment `TRNSYS` (to allow for the intermittent heating of the behavioural model) in which a two-zone building is modelled (to allow for the zonal heating). To enable easy implementation –a prerequisite for application in a probabilistic bottom-up housing stock framework– the building model is conceived as generic as possible and all pre- and postprocessing steps are controlled for in `MATLAB`.

In order to keep total calculation time manageable, some simplifications were made. Air flows are not modelled in detail; the infiltration heat losses are assessed using the Lawrence Berkeley National

Laboratory (LBNL) Infiltration model, while the ventilation losses are pragmatically estimated by relying on a Belgian measurement campaign of ventilation systems. Also, no space heating system is modelled; `TRNSYS` is only used to compute the net energy demand by means of an ideal heating equipment, after which an overall heating system efficiency, varying throughout the year as a function of the monthly gains over losses ratio, is applied to convert the net demand to an energy use.

Evaluation of the improved prediction model of energy use for space heating

Based on a small case study district, simulation results were generated and a *comparison with measurements* was carried out. Regarding the indoor temperature, a satisfying agreement was found for the dayzone temperatures, while a smaller correspondence was found for the nightzone temperatures. For the latter, hypotheses were formulated, none of which can be said to have predominant impact. Regarding the energy use for space heating, it was observed how large individual errors were found for a set of individual dwellings, denoting how the developed methodology is not meant to predict the energy use in specific single cases. When however the simulation results were compared to a large-scale Belgian measurement campaign, a satisfactory correspondence was observed.

To evaluate to what extent the developed methodology is a more trustworthy alternative compared to energy labelling tools, a *comparison with the Belgian energy performance assessment regulation* (EPR 2010) was performed. The developed methodology generates energy uses for space heating that are, for poorly insulated dwellings, about 25 % lower than those from the EPR. With the actual energy uses proving to be about 50-60 % lower than those from the energy labelling tools, it is shown how the developed methodology is able to reduce a significant part of the pre-retrofit energy performance gap. In the case of only insulating the roof areas −still a popular retrofit measure in Belgium− the calculated energy savings proved to be only 30 to 50 % of those from the EPR, corresponding to a large shortfall in expected energy savings of 70 to 50 %. In the case of a more thorough renovation of the building envelope, the energy savings were about 75 % of those from the EPR, corresponding to 25 % shortfall. Since actual shortfall is found to vary between 20 to 60 %, the here developed methodology is able to account for a significant part of it, as such yielding more reliable energy saving predictions.

Application within a probabilistic bottom-up housing stock modelling framework

In order to deal with the large heterogeneity inherent to housing stocks, a new technique, called the *stochastic* technique, is proposed and investigated. Given the generic set up of the building model and the available probabilistic behavioural model, this stochastic technique can easily capture both user and dwelling variability and has proven to be an elegant and straightforward way of generating an aggregated output, independently of the scale desired (city/district/regional/national). When applied on a subgroup of the Belgian housing stock, the generated outcome is very comparable to that of the sample technique and outperforms the archetype technique. This stochastic technique also offers interesting opportunities concerning the data gathering process. Instead of requiring a single large-scale and highly detailed housing database, different (currently available) data sources could be combined –if of course representing a similar population– to feed the required probability input distributions of the stochastic technique.

Finally, it was pointed out that, despite uncertainty being an intrinsic feature of bottom-up housing stock modelling, it is only rarely considered as point of attention when setting up such models and there is no widely spread framework about how uncertainty should be incorporated. A framework is provided to do so, in which the 'hyper'-parameters of the housing stock model itself are being questioned and in which the determination of the total housing stock energy use is required under different, yet not necessarily less plausible submodels, assumptions, databases etc. By doing so, the computed results can be put in the wider perspective of actual modelling reality, thereby contributing to more robust and informed policy making.

Main conclusions

When aiming at more reliable energy saving predictions in a housing stock context, this research work has shown that a dynamic two-zone building model, in which an evidence-based probabilistic behavioural model is implemented, forms a more trustworthy prediction method than the currently used and highly simplified energy labelling tools. The main reasons are:

- the implementation of zonal and intermittent heating patterns, evidence-based whenever possible and allowing for a more realistic representation of actual (Belgian) heating behaviour;
- the probabilistic approach in modelling the user behaviour, which avoids the often arbitrary definition of a standard/average user and which leads to more useful output concerning robust policy making, because energy uses and savings are rightfully represented as probability distributions rather than deterministic values;
- the inclusion of a correlation matrix, which, although it cannot completely capture the real-life complexity, offers an interesting methodological framework for stochastically linking behavioural, sociological and building parameters;
- the use of a dynamic building energy simulation environment, eliminating the need for error inducing utilization and correction factors (as needed in the quasi-steady state methods) and allowing for the automatic incorporation of the physical part of the temperature takeback.
- given the probabilistic approach, an upscaling towards full-scale housing stock models can easily include both the large user and dwelling heterogeneity, inherent to housing stocks, as such leading to a more reliable assessment of the housing stock estimates.

In order to make affirmative statements about how this improved prediction method relates to actual energy uses at the aggregated level, additional research is required, but the preliminary comparisons in this dissertation are promising. Hence, given the above features and intrinsic opportunities of the developed methodology, a dynamic and probabilistic approach proves to be highly worthwhile when setting up a housing stock model that is to be used in a policy making context.

Finally, it must kept in mind that the above conclusions do not imply that the energy labelling tools should be abandoned. As long as these tools are not used as a predictive tool, there is no interference with their true purpose: assessing an objective energy performance label to individual buildings and their systems, independently of the inhabitants and their behaviour. Of course, since beside that purpose, these energy labelling tools are very often also used by architects and individual house-owners to assess the influence of possible retrofitting measures, certain rather straightforward improvements (like adaptations to the single zone temperature, dropping hygienic ventilation losses when no ventilation system is present, ...) could be considered in order to generate at least more plausible energy uses and savings.

Main limitations and perspectives for future research

- The presented results strongly rely on the probabilistic behavioural model, so its limitations should be kept in mind: (i) the real-life variation in spatial zoning patterns is not fully accounted for; (ii) temporary variations in the occupancy profiles like holidays, daytrips or short-term manual adaptations to the settings are not included; (iii) the model is set up whilst keeping the typical Belgian central heating system in mind. This implies that adaptive behaviour to the type of heating system and temperature control is not included; (iii) some important parameters are implemented simplified (internal heat gains) and/or are highly uncertain (nightzone heating behaviour, window opening behaviour). It is evident that, in order to tackle its limitations, additional refinements to the model are possible and should be investigated, thereby preferably relying on large-scale survey and/or measurement campaigns that can clarify the true extents of the uncertain input parameters.

- Another field for future work consists of improvements to the building model. In this dissertation a pragmatic and empirical approach is adopted regarding the convective heat losses of window opening behaviour and hygienic ventilation. Also, interzonal air flows have not been considered, leading to a rigid separation of day- from nightzone air and hence, possibly exaggerating the gap between the adopted two-zone and traditional single-zone modelling approach. Finally, the heating system is included only through an overall heating system efficiency, which can only limitedly account for user behaviour actions influencing its operation.
  Hence, important challenges lie in investigating whether more detailed (sub)models could and should be used within the building model, whilst still preserving its overall applicability in a bottom-up housing stock context.

- In the presented work, focus is put in assessing the *pre-retrofit* energy use for space heating, hence mainly trying to capture what happens in poorly insulated dwellings. For (very) low energy houses however, the applicability must be revised, because the behavioural parameters, the installed heating/ventilation systems and their mutual interactions, can be substantially different. For instance, other behavioural profiles might be needed, focusing less on heating preferences, yet more on detailed internal heat gains emission of both occupants and appliances, window opening behaviour, the opening of internal doors etc. Also, additional user behaviour actions, like lowering sun screens to reduce overheating (more prevailing in low energy houses), might have to be considered. Finally, due to the higher impact of solar gains and certainly when looking at strongly urbanized locations, it might be necessary to include obstacles, overhangs, surrounding buildings etc. within the simulation model, in order to more reliably assess the energy saving potential of retrofits towards (extremely) low energy standards.

- In this dissertation the focus is restricted to residential energy use for space heating. Especially when aiming for a more complete characterisation of the total energy saving potential of the residential building sector, it is evident how further extensions towards appliances and hot tapwater should be integrated.

- The overall reliability of the methodology would benefit from a more extensive comparison with measurement data. Such comparison is preferably carried out on an aggregated level, requiring a large-scale and sufficiently detailed housing database with corresponding energy consumption data.

- A final field for future research focusses on the uncertainty quantification of the housing stock model estimates. A general set-up to do so is provided in this work, meant to initiate further research on how the uncertainty, inherent to housing stock and their models, can be quantified and communicated.

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Education

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2002 – 2007	Master of Civil Engineering University of Leuven, Belgium (great distinction) M.Sc Thesis: *The Rebound Effect (in Dutch)*
1996 – 2002	Latin - Mathematics Sint-Romboutscollege, Mechelen, Belgium

Present and previous positions

2010 – 2015	Ph.D. student at the Section of Building Physics Department of Civil Engineering, University of Leuven, Belgium
2007 – 2010	Researcher at the Section of Building Physics Department of Civil Engineering, University of Leuven, Belgium

Distinctions and Awards

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Scientific publications

International journal publications

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